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Machine Learning to Predict the Need for Postmastectomy Radiotherapy after Immediate Breast Reconstruction

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Background: Post mastectomy radiotherapy (PMRT) is an independent predictor of reconstructive complications. PMRT may alter the timing and type of reconstruction recommended. This study aimed to create a machine learning model to predict the probability of requiring PMRT after immediate breast reconstruction (IBR).

Methods: In this retrospective study, breast cancer patients who underwent IBR from January 2017 to December 2020 were reviewed and data were collected on 81 preoperative characteristics. Primary outcome was recommendation for PMRT. Four algorithms were compared to maximize performance and clinical utility: logistic regression, elastic net (EN), logistic lasso, and random forest (RF). The cohort was split into a development dataset (75% of cohort for training-validation) and 25% used for the test set. Model performance was evaluated using area under the receiver operating characteristic curve (AUC), precision-recall curves, and calibration plots.

Results: In a total of 800 patients, 325 (40.6%) patients were recommended to undergo PMRT. With the training-validation dataset (n = 600), model performance was logistic regression 0.73 AUC [95% confidence interval (CI) 0.65–0.80]; RF 0.77 AUC (95% CI, 0.74–0.81); EN 0.77 AUC (95% CI, 0.73–0.81); logistic lasso 0.76 AUC (95% CI, 0.72–0.80). Without significantly sacrificing performance, 81 predictive factors were reduced to 12 for prediction with the EN method. With the test dataset (n = 200), performance of the EN prediction model was confirmed [0.794 AUC (95% CI, 0.730–0.858)].

Conclusion: A parsimonious accurate machine learning model for predicting PMRT after IBR was developed, tested, and translated into a clinically applicable online calculator for providers and patients. *(Plast Reconstr Surg Glob Open 2024; 12:e5599; doi: 10.1097/GOX.0000000000005599; Published online 6 February 2024.)*

INTRODUCTION

Over the last decade, there has been a notable increase in the rates of immediate implant-based breast reconstruction (IBR),[1–4] given its impact on quality of life and oncologic safety profile.[5,6] One of the main challenges of IBR is the long-term morbidity, which may result after postmastectomy radiotherapy (PMRT).[7] As an independent predictor of reconstructive complications, PMRT is associated with higher rates of reconstructive failure, infection, implant exposure, capsular contracture, and mastectomy flap necrosis.[7,8] The need for PMRT may alter both the timing and type of reconstruction recommended to optimize long-term outcomes.[1,9–14]

In the setting of early breast cancer, the need for PMRT is not known preoperatively. Indications for PMRT depend primarily on postoperative pathologic staging following oncologic resection. For patients with invasive breast cancer and four or more positive lymph nodes and/or a tumor greater than 5 cm, the benefit of PMRT has been

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well established.[15] However, PMRT for patients with one to three positive lymph nodes is debated,[16,17] as the absolute benefit may not outweigh potential toxicities.[18] Other patient and tumor characteristics may also influence the recommendation for PMRT including age, location of primary tumor, margin status, hormone receptor status, presence of lymphovascular invasion, extranodal extension, internal mammary lymphadenopathy, number of axillary lymph nodes removed, and size of largest deposit of axillary nodal disease.[19,20] The majority of patients for whom IBR is offered are early-stage and clinically node negative but are often found to have one to three pathologically positive lymph nodes.[17] Predicting whether PMRT will be indicated is difficult for the most common clinical presentation.[2,3] Preoperative prediction of the need for PMRT would inform shared decision-making for the type and timing of reconstructive surgery.[14]

Machine learning (ML) prediction models generate individualized risk profiles based on group-level evidence.[21] ML modeling has been applied for predicting breast cancer outcomes, including risk of diagnosis,[22,23] prognosis,[24] treatment adherence,[25] and treatment morbidity.[26] In this present study, we sought to create an ML model to predict the probability of requiring PMRT after IBR. Secondarily, we aimed to compare the performance of ML to traditional regression methods for prediction modeling in this clinical setting.

Takeaways

Question: Postmastectomy radiotherapy (PMRT) is an independent predictor of reconstructive complications. Can the need for PMRT be predicted preoperatively to inform shared decision-making for the type and timing of breast reconstructive surgery?

Findings: A machine learning (ML) model for predicting PMRT was developed, tested, and translated into a clinically applicable online calculator for providers and patients. The ML model quantifies the risk based on the relative importance of preoperative predictors and aggregates these contributions into a combined statistical score.

Meaning: This ML prediction model may be used clinically to provide an individualized patient risk of PMRT during the preoperative discussion of reconstructive options.

METHODS

Study Population

This is a single institution, multisite, retrospective cohort study of breast cancer patients who underwent mastectomy with immediate alloplastic breast reconstruction from January 2017 to December 2020. Institutional research ethics approval was obtained. Patients with a diagnosis of breast cancer underwent skin or nipple-sparing mastectomy with one or two-stage alloplastic breast reconstruction. Patient exclusion criteria were prophylactic mastectomy, delayed reconstruction, autologous reconstruction, and contraindications for PMRT, including history of chest wall irradiation, connective tissue disorder, pregnancy, in situ pacemaker, and severe lung disease precluding chest radiation therapy. Patients undergoing autologous reconstruction were excluded to reduce the potential confounder of reconstructive type influencing the recommendation for PMRT. All mastectomies were conducted by a group of nine surgical oncologists and six plastic surgeons. All patients undergoing IBR had acellular dermal matrix used as an adjunct in the reconstructed breast mound.

Primary Outcome

Recommendation for PMRT, as opposed to receipt of PMRT, was selected as the primary outcome for prediction in this study. A group of five radiation oncologists provided recommendations for PMRT based on patient characteristics and postoperative pathologic staging in accordance with national guidelines.[19,27] For early-stage breast cancer, recommendations for PMRT are based on an objective evaluation of the patient characteristics and tumor pathology after resection. In shared decision-making, patient preference and autonomy is paramount and may trump clinician recommendations according to PMRT indications. Thus, we selected PMRT recommendation, as opposed to PMRT receipt, for our primary outcome to facilitate the generation of a prediction model based on objective clinicopathological data.

Risk Factors for PMRT

Patients were categorized into two groups according to the recommendation for PMRT. A total of 125 factors (81 preoperative and 44 postoperative risk factors) were considered of potential importance for interpreting the recommendation for PMRT. Only preoperative risk factors were used to generate the prediction model. Preoperative risk factors were recorded for patient and tumor characteristics derived from clinical history, physical examination, diagnostic imaging, and biopsy pathology. Preoperative data included demographics, age of diagnosis, menopausal status, genetic susceptibility, and tumor palpability. Diagnostic imaging reports were reviewed, and data recorded for type of imaging [mammogram, ultrasound, magnetic resonance imaging (MRI), tumor size (maximum dimension)], focality, and number of foci. Preoperative biopsy data was recorded for type (core or open), grade, histologic subtype, estrogen, and progesterone receptor status, human epidermal growth factor receptor 2 (HER2) status. Treatment data were recorded for type of mastectomy, receipt of neoadjuvant chemotherapy, and planned axillary surgery. Also, the final postoperative pathology characteristics were recorded to evaluate congruence with PMRT recommendations and serve as an interval validation of the clinicopathologic features that led to the PMRT recommendation. All data points collected are summarized and defined in Supplemental Digital Content 1. (**See table 1, Supplemental Digital Content 1,** which displays the data dictionary defining preoperative variables used to generate prediction model and postoperative variables used to internally validate the congruence between

PMRT recommendation and PMRT receipt based on indications. **http://links.lww.com/PRSGO/D62**.)

All data, including primary outcome and predictor variables, were collected directly from the medical records and stored in the Research Electronic Data Capture database.[28]

Statistical Analysis

Descriptive statistics were used to present continuous variables as a median (range) and categorical variables as proportions. Using the development cohort, patients with and without a recommendation for PMRT were compared. Three composite features (preoperative lymph node positivity, preoperative lymph node size, and maximum tumor size) were created to consolidate values across imaging modalities (mammogram, ultrasound, positron emission tomography). Thus, 81 preoperative factors were reduced to 54 factors to reduce overfitting. Values missing at random were imputed using either logic-based rules[29] or using the ML algorithm multivariate k-nearest-neighbor algorithm[30] which leverages any available information to predict the missing value. Values missing with a known rationale were defined as "unknown" and not imputed (eg, ER, PR, and HER2 statuses were not routinely determined for patients with DCIS undergoing a mastectomy). Patient and tumor characteristics were summarized using descriptive statistics. For this first discovery study, sample size calculation was not performed given the absence of effect size estimates and the separation of these distributions in the published literature for ML model prediction.

Prediction Model Development

To predict the need for PMRT, four ML/statistical algorithms were applied: logistic regression (LR),[31] elastic net (EN),[32] logistic lasso (LL),[33] and random forest (RF),[34] which are standard algorithms among ML practitioners.[35] Compared with LR, LL facilitates regularization to find a smaller model with fewer features. EN combines LL with ridge regression, which allows multiple correlated features to be selected.[35] Feature importance scores were computed to assign a score to each preoperative variable representing its importance in predicting the likelihood of PMRT. For importance scores, a larger magnitude signifies a stronger influence; a positive score indicates higher likelihood of PMRT recommendation, whereas a negative score indicates lower likelihood of PMRT. Importance scores were computed by standardizing regression coefficients. Training and validation were performed with five repetitions of stratified 10-fold cross-validation procedure. The entire cohort was split into a development dataset and a test dataset by random computer selection, with 75% of patients analyzed for the development of the prediction models (training-validation) and 25% used for the testing of the models. Once developed, the trained prediction models were frozen and evaluated on the test dataset. There was no overlap between patient sources of the training-validation and test datasets.

Performance Evaluation

The area under the receiver operating characteristic curve (AUC) was used as the performance metric for evaluation, comparison, and selection of models.[36] Additional evaluations for model performance included precision and calibration. Precision-recall curves were used to evaluate the trade-off between precision and sensitivity at defined thresholds. Calibration plots were used to compare the models' probabilistic predictions and the true PMRT recommendation probability, with perfect calibration defined by a plot of a 45-degree line.

RESULTS

Patient characteristics

A total of 800 breast cancer patients undergoing IBR were included in the study cohort. (**See figure, Supplemental Digital Content 2,** which displays the flow chart of eligible, included, and excluded patients. PMRT: postmastectomy radiotherapy; IBR: immediate breast reconstruction. **http://links.lww.com/PRSGO/D63**.)

At the time of mastectomy, 90% of patients underwent tissue expander placement and 10% underwent definitive implant placement. Patient and tumor characteristics are outlined in Table 1. At presentation, 59% had a palpable tumor and 10% underwent investigations for a palpable axillary lymph node. Tumor size was a median of 20 mm on both mammogram and ultrasound (range 1–25 mm, 1–54 mm respectively). Preoperative biopsy with core needle was most common (88.2%), with invasive ductal carcinoma as the most frequent histologic diagnosis (64.1%) of moderate grade. Among the entire cohort of 800 patients, a total of 325 (40.6%) patients were recommended to undergo PMRT. Based on postoperative pathology, indications for PMRT were most frequently the presence of positive axillary lymph nodes (51%), a tumor size greater than 5 cm (29%), and lymphovascular invasion (26%), with some patients having multiple indications. [**See table 2, Supplemental Digital Content 3,** which displays the indications for PMRT based on patient characteristics and postoperative pathologic features (n = 325 patients recommended to receive PMRT). **http://links.lww.com/PRSGO/D64**.]

Model Development and Feature Selection for Predicting PMRT

The training-validation dataset of 600 patients was used to optimize model and feature selection. All preoperative factors were initially considered as predictors. Four models, LR, LL, EN, and RF, were trained and evaluated using repeated 10-fold cross-validation. Model performance was LR algorithm, 0.73 AUC [95% confidence interval (CI) 0.65–0.80]; RF, 0.77 AUC (95% CI, 0.74–0.81); EN, 0.77 AUC (95% CI, 0.73–0.81); LL, 0.76 AUC (95% CI, 0.72–0.80). Regularization incentivizes EN and LL to select only the most predictive preoperative factors. Without significantly compromising performance, the 81 predictive factors could be reduced to a minimum of 12 for the EN method (Table 2) and 13 for prediction with the LL method, and over 50 variables were selected using each RF and LR models.

Features selected by model algorithms were further verified for congruence with clinical knowledge. The features of greatest importance in predicting the need for

Table 1. Preoperative Patient and Tumor Characteristics (n = 800 Patients)

Characteristic	n (%)
Age	49.3 (26–79)
BMI	24.0 (17.1–41.6)
Menopausal status	
Premenopausal	425 (53.1)
Postmenopausal	373 (46.7)
Family history of breast cancer	290 (36.7)
Genetic mutation carrier	
BRCA 1	25 (3.1)
BRCA 2	2 (0.3)
p53	9 (1.1)
Palpability	
Tumor	460 (59.2)
Axillary lymph node	81 (10.1)
Diagnostic imaging	
Mammography	706 (88.3)
Ultrasound	615 (76.9)
MRI	27 (3.4)
Tumor size on mammogram, mm	20 (1–25)
Tumor size on ultrasound, mm	20 (1–54)
Histology	
IDC	513 (64.1)
ILC	66 (8.3)
In situ	218 (27.3)
Tumor grade	
1	185 (24.5)
2	399 (52.8)
3	211 (27.9)
Tumor focality	
Multifocal	161 (20)
Preoperative biopsy type	
Core needle biopsy	796 (88.2)
Excisional surgical biopsy	93 (11.8)
HER2 status	
Positive	148 (18.5)
Negative	503 (62.9)
Unknown	149 (18.6)
Estrogen status	
Positive	618 (77.3)
Negative	132 (16.5)
Unknown	50 (6.3)
Progesterone status	
Positive	480 (60.0)
Negative	198 (24.8)
Unknown	122 (15.3)
Neoadjuvant chemotherapy	180 (22.5)
Planned nipple-sparing mastectomy	277 (35)
Planned sentinel lymph node biopsy	643 (80)

PMRT recommendation included the presence of metastasis on preoperative axillary biopsy, palpable axillary lymphadenopathy, and a negative HER2 receptor status. Tumor size and size of any present suspicious lymph node were also highly predictive of need for PMRT. Ultrasound as an initial diagnostic modality, any invasive histology, and presence of lymphovascular invasion on core biopsy were additionally predictive of PMRT. Features predicting against the need for PMRT included a histology of DCIS, having undergone a core biopsy (as opposed to excisional biopsy), older age, and a negative ER status. Frequency of each feature is summarized in Table 3 according to recommendation for PMRT.

Table 2. Optimal Features Selected by the ML Algorithm EN

Feature	Importance
Presence of carcinoma on axillary lymph node biopsy	0.24046
Histology: DCIS	−0.23067
Presence of preoperative palpable axillary lymph node	0.20967
HER status: negative	0.15977
Maximum dimension/size of preoperative tumor (mm)	0.15503
Histology: IDC	0.1547
Maximum size of preoperative suspicious lymph node (mm)	0.1276
Tumor biopsy method	−0.1208
Initial diagnostic imaging modality: ultrasound	0.1221
Presence of lymphovascular invasion	0.02746
Age at diagnosis	−0.02471
ER status: negative	−0.01126

Model Performance and Validation

Model parameters obtained during cross-validation were frozen and applied on the test dataset of 200 patients to predict the probability of PMRT. On the test dataset, both EN and LL evaluated to 0.794 AUC (95% CI, 0.730–0.858, 95% CI, 0.728–0.859) with parsimonious feature selection as compared to the other two algorithms [LR, 0.729 AUC (95% CI, 0.652–0.905); RF, 0.802 AUC (95% CI, 0.739–0.864)]. With the fewest features, the EN model achieved high performance as visualized in calibration (Fig. 1a) and AUC curves (Fig. 1b) with 12 features. In comparison, the RF model achieved the highest AUC of 0.802 but necessitated 54 preoperative features for its prediction of PMRT. Given the LL model with 13 features did not significantly outperform the EN model, the EN model, due to its simplicity, was used to create a nomogram calculator based on the standardized coefficients (available online for real-time use at https://surgery.med.ubc.ca/divisional-research/plastic-surgery/pmrt-nomogram/).

DISCUSSION

In the era of personalized medicine, patients seek information tailored to their individualized risk. In the setting of IBR, PMRT is an independent predictor of reconstructive failure and poor long-term outcomes.[7,8] To help guide preoperative shared decision-making, we have developed an online nomogram for predicting the recommendation for PMRT for patients seeking IBR. Our preferred EN prediction model is parsimonious, accurate, and clinically useful, as it is based on preoperative data available and accessible at the time of reconstructive consultation. The EN online nomogram can be used in real-time during discussion with patients.

Clinical Utility

Prediction models facilitate shared decision-making in breast reconstruction by risk profiling surgical morbidity[21,37–39] and have also been used to guide treatment

Table 3. Frequency of Predictive Features for "PMRT Recommended" and "No PMRT Recommended" Groups (n = 800)

Features	PMRT Recommended	
	Yes n (%)	No n (%)
Presence of metastasis on axillary biopsy	85 (21.6)	23 (2.8)
Palpable axillary lymphadenopathy	54 (6.7)	27 (3.3)
Negative HER2 receptor status	242 (30.3)	261 (32.6)
Negative ER receptor status	58 (7.2)	74 (9.3)
Presence of suspicious lymph node	92 (11.5)	29 (3.6)
Ultrasound as initial diagnostic modality	288 (36)	327 (40.9)
Invasive histology	288 (36)	297 (37.1)
Presence of lymphovascular invasion	146 (18.2)	321 (40.1)
DCIS histology	35 (4.4)	180 (22.5)
Core biopsy	212 (26.5)	433 (54.1)
Age >40*	195 (24.4)	324 (40.5)
Tumor size*		
<2 cm	100 (12.6)	237 (30.0)
2–5 cm	178 (22.3)	171 (21.4)
>5 cm	68 (8.6)	37 (4.7)
Total	325 (40.6)	475 (59.4)

*Age and tumor size were input as continuous variables in prediction model but categorized for presentation in this table.

decisions in cancer care[40–43] and chronic care.[44–48] Given the impact of PMRT on long-term reconstructive outcomes, the ability to predict its use is invaluable in guiding decisions on the timing and type of reconstruction and informing our discussion of risks.[14] This ML prediction model may be used clinically to provide an individualized patient risk of PMRT during the preoperative discussion of reconstructive options. The ML model quantifies the risk based on the relative importance of predictors and aggregates these contributions into a combined statistical score. We believe this score may assist in shared decision-making. An immediate, delayed, or immediate delayed approach may be chosen based on the preoperative determined likelihood of PMRT.[14,49] Adjuvant radiation was previously considered to be a relative contraindication for IBR, favoring a delayed reconstructive approach.[1,11] For immediate reconstruction, risk profiling will differ for those receiving PMRT, regardless of reconstructive type.[14,39,50] Autologous reconstruction may be favored in the setting of anticipated PMRT, given a reduced level of morbidity as compared to alloplastic reconstruction.[51–53] Recent studies report that alloplastic reconstruction remains the predominant form of breast reconstruction in the setting of radiation[54] and support successful completion of reconstruction.[55] However, long-term patient satisfaction and health-related quality of life is reduced after alloplastic reconstruction and PMRT when compared with those without PMRT exposure.[53] Thus, the findings of this study may be used clinically to inform patients of their individualized risk of PMRT based on preoperative information. For example, a 40-year-old patient interested in IBR presenting with a 30-mm invasive ductal carcinoma (ER+/Her2+) with lymphovascular invasion diagnosed by mammogram and core biopsy, with no suspicious axillary lymphadenopathy, would have a predicted probability of 40% of needing PMRT. This individualized predictive moderate risk of PMRT may support the patient in avoiding implant-based reconstruction and undergoing an autologous reconstruction to avoid the risks of capsular contracture or reconstructive failure.[9,12,13,50] Although our present study provides a strategy for informing these important decisions, further validation is required and planned in an external cohort to assess generalizability of our findings before deployment of the model.

A minority (3%, n = 10) of patients recommended for PMRT elected not to undergo radiation therapy. We purposefully selected "recommendation for PMRT" as opposed to "receipt of PMRT" as we had hypothesized that some may elect not to receive radiation despite recommendations. The prediction model is based on objective preoperative findings and aims to facilitate decision-making in the preoperative setting with an individualized predictive risk of being recommended for PMRT. However, the receipt of PMRT will be based on tumor pathology after resection, patient characteristics, preferences, and goals in the shared decision-making process.

Model Development

Multifactor regression models based on population cohorts provide epidemiological evidence to guide shared decision-making. However, they do not provide an individualized probability of an outcome. Furthermore, traditional regression models are inherently limited by mathematical assumptions including linearity and homogeneity of variance.[56] Machine-learning algorithms may provide a higher level of prediction accuracy by capturing complex linear and nonlinear relationships in clinicopathological data. Accordingly, ML prediction models have been used for prognosticating outcomes of survival, recurrence, and morbidity in cancers of the breast,[23,24] colorectal cancer,[57,58] and lung cancer.[59–61] Regression-based prediction models include LR, EN, and LL. Due to their normalization penalties, LL and EN prefer to shrink the estimated coefficients as much as possible given the same level of estimation error, thus minimizing overfitting. We experimented with varying regularization

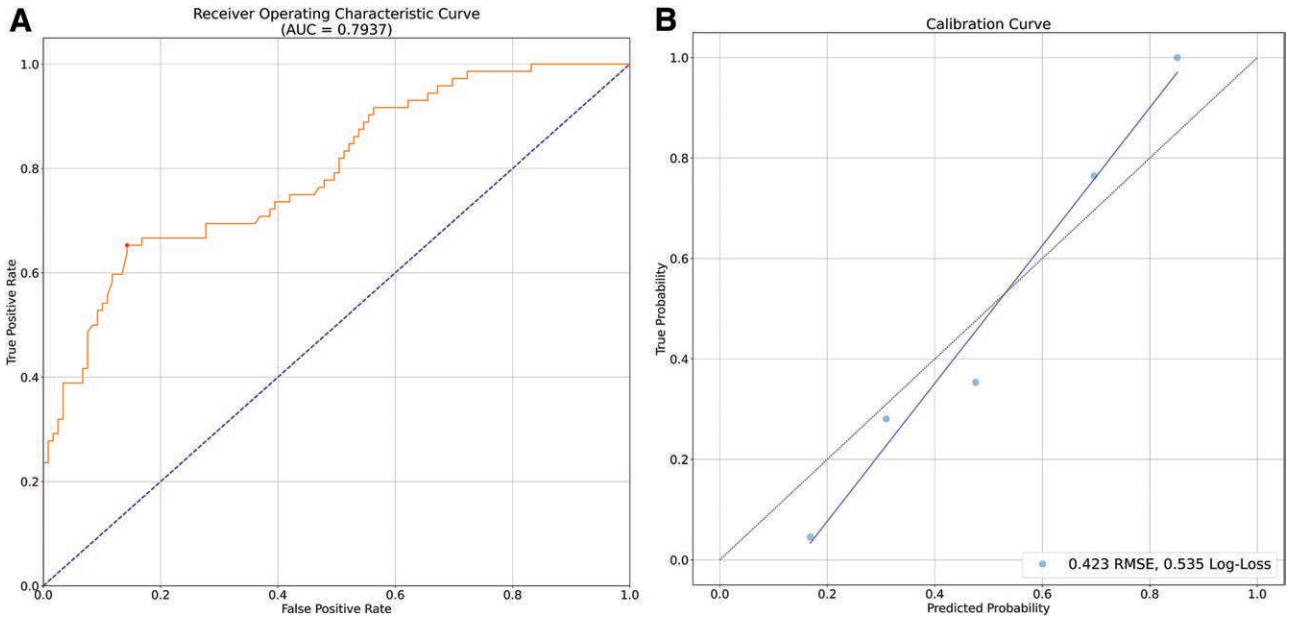

Fig. 1. Performance of the optimal model using EN as visualized on calibration (A) and AUC curves (B) with 12 features.

strengths (λ of LL, and the L1-to-L2 mixing parameter of EN) using a grid-search over candidate configurations. RF builds an ensemble of decision trees, and is capable of modeling complex, nonlinear relationships. RF has been used in the biomedical domain.[62] RF offers little interpretability but serves as a strong performance ceiling for the regression models. Thus, despite the high performance of RF, LL and EN are preferred for achieving a balance of parsimony and accuracy. Recall that the key difference between LL and EN is how correlated features are allowed to be included in the model. Due to its simplicity, we selected EN for the online nomogram. Of note, the model did not account for differences in the oncologists providing the PMRT recommendation, nor for the surgeons performing the mastectomy or reconstruction. In our center, the radiation oncologists are a small group of five individuals with a high-volume clinical practice of breast cancer patients and homogeneity in their application and implementation of guidelines for PMRT recommendation. Surgeon factors were not considered because the predictive variables are not influenced by a surgeon's technique.

Risk Factors for PMRT

Not all preoperative factors were relevant to prediction of PMRT. Feature selection reduced the number of required input factors from 81 to 12 for EN and 13 for LL. The EN and LL models performed equally well using either the reduced or the full feature set. A nomogram calculator was created using the reduced feature set to facilitate use in the clinical setting. Clinical correlation with the ML selected features is essential for salience, interpretability, and application of the prediction model. In this study, features predictive of PMRT recommendation pertained to the presence of metastasis on preoperative axillary biopsy, palpable axillary lymphadenopathy, and the size of any present suspicious lymph node. Notably, patients with presence of metastatic carcinoma on axillary lymph node biopsy or palpable lymphadenopathy did not always receive PMRT recommendation, explained by a negative postoperative lymph node status. Tumor size was highly predictive of need for PMRT. Maximal tumor dimension from any imaging modality was used in the model given that mammogram, ultrasound, and MRI differ in their accuracy of tumor size estimation.[63] Interestingly, ultrasound as an initial diagnostic modality was most predictive when compared with other modalities, which may be explained by the underestimation of size with mammogram and overestimation of size with MRI.[63,64]

Limitations

To assess the clinical utility of an ML algorithm, not only its performance in recapitulating historical events must be evaluated but also its accuracy of predicting future events. This model was trained, evaluated, and tested using a dataset derived from a single institution. Although there are standardized indications for PMRT in breast cancer care, there may heterogeneity in the guidelines or implementation of these standards at national and international levels.[15] A larger and multi-institutional dataset would allow the fitted models to better generalize to other patient distributions.[21] Our prediction model is based on objective clinicopathologic features and did not account for the risk tolerance of either the patient or the radiation oncologist recommending PMRT. It is unknown if PMRT recommendations are influenced by a planned or desired reconstruction and how patients integrate the risks of reconstructive morbidity in discussions with their radiation oncologist. With a study cohort derived from a single institution, these potential PMRT recommendation biases are minimized. Given this may limit the

generalizability of our prediction model, further external validation is planned. Given the absence of effect size estimates available for sample size calculation in this discovery study,[65] we based our cohort size on other prediction ML models of similar complexity[66] and applied strategies to minimize overfitting.[67] In subsequent validation, we will use the estimates of effect size and their distribution to inform our target sample size. Finally, it is important to emphasize that the final recommendation for PMRT is based on postoperative pathology results, which is an inherent limitation of prediction models in a preoperative setting.

CONCLUSIONS

ML was applied for predicting the recommendation for PMRT. A parsimonious accurate prediction model was developed, tested, and translated into a clinically applicable online nomogram calculator for use by providers and patients. Relevant features for predicting PMRT are readily available in preoperative consultation, including tumor size, diagnostic modalities used, suspicion of axillary lymph node metastasis, HER2 and ER status, and histology subtype. Clinical application of this prediction model may be invaluable for shared decision-making in breast reconstruction consultation.

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DISCLOSURES

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