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Breast

Using a Machine Learning Approach to Predict the Need for Elective Revision and Unplanned Surgery after Implant-based Breast Reconstruction

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Summary: Two-stage implant-based reconstruction after mastectomy may require secondary revision procedures to treat complications, correct defects, and improve aesthetic outcomes. Patients should be counseled on the possibility of additional procedures during the initial visit, but the likelihood of requiring another procedure is dependent on many patient- and surgeon-specific factors. This study aims to identify patient-specific factors and surgical techniques associated with higher rates of secondary procedures and offer a machine learning model to compute individualized assessments for preoperative counseling. A training set of 209 patients (406 breasts) who underwent two-stage alloplastic reconstruction was created, with 45.57% of breasts (185 of 406) requiring revisional or unplanned surgery. On multivariate analysis, hypertension, no tobacco use, and textured expander use corresponded to lower odds of additional surgery. In contrast, higher initial tissue expander volume, vertical radial incision, and larger nipple-inframammary fold distance conferred higher odds of additional surgery. The neural network model trained on clinically significant variables achieved the highest collective performance metrics, with ROC AUC of 0.74, sensitivity of 84.2, specificity of 63.6, and accuracy of 62.1. The proposed machine learning model trained on a single surgeon's data offers a precise and reliable tool to assess an individual patient's risk of secondary procedures. Machine learning models enable physicians to tailor surgical planning and empower patients to make informed decisions aligned with their lifestyle and preferences. The utilization of this technology is especially applicable to plastic surgery, where outcomes are subject to a variety of patient-specific factors and surgeon practices, including threshold to perform secondary procedures. *(Plast Reconstr Surg Glob Open 2024; 12:e5542; doi: 10.1097/GOX.0000000000005542; Published online 19 March 2024.)*

MACHINE LEARNING TO PREDICT SECONDARY PROCEDURES

Two-stage implant-based breast reconstruction is one of the most common reconstructive pathways after mastectomy, in which tissue expanders are placed at the time of mastectomy and later exchanged for permanent implants.[1,2] However, oftentimes patients will undergo more than the two planned procedures. In a recent prospective case series, Fischer et al found that, in comparison with autologous and direct-to-implant reconstructions, patients undergoing two-stage tissue expander reconstruction had the highest rate of unplanned revisions at 59.2%, encompassing both cosmetic and complication-driven revisions.[3] Revisional procedures not only add unexpected cost—one study found that revision procedures for implant-based reconstruction added as much as 74.1% additional healthcare costs—but also are associated with lower patient satisfaction.[4,5] Therefore, there exists a need to predict a patient's risk of secondary procedures to guide preoperative counseling and expectations.

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Multivariate analyses of risk factors for postoperative complications and revision procedures offer some guidance, but are difficult to apply clinically, particularly when patients have opposing factors that may increase or decrease the likelihood of the particular outcome analyzed. Recent advances in artificial intelligence offer promising methods of analyzing large institutional cohorts and precisely determining the likelihood of outcomes based on specific patient profiles.[6–9] In this study, we present a machine learning model that can compute individualized risk assessments for preoperative counseling. In a highly personalized field such as plastic surgery, artificial intelligence offers a currently underutilized opportunity to provide patient- and surgeon-specific evaluations.

Takeaways

Question: What are the key predictors of secondary revision procedures among postmastectomy patients who elect to undergo two-stage, prosthesis-based reconstruction, and can we provide a personalized risk assessment using machine learning?

Findings: Never smoking, hypertension, and textured expander corresponded to lower odds of undergoing revision surgery. In contrast, higher initial tissue expander volume, vertical radial incision, and larger nipple-inframammary fold distance conferred higher odds of needing additional procedures. Additionally, we built a machine learning model to predict individualized risk.

Meaning: Machine learning models enable physicians to adapt surgical plans, foster better communication, and help patients make informed decisions that align with their lifestyle and preferences.

METHODS

The training set for this model was created by retrospective chart review of 209 patients (406 breasts) who completed two-stage implant-based reconstruction with the senior author (D.M.O.) at a tertiary-care facility between 2012 and 2021. Demographic information and operative details were collected from the electronic medical record for each patient.

The primary outcome was additional breast procedures performed within a 2-year window after implant exchange; these included cosmesis-driven and complication-driven procedures. Multiple procedures performed during the same encounter (eg, concurrent mastopexy and fat grafting on the same breast during the same operation) were counted as one additional surgery. Revision surgery details are highlighted in Supplemental Digital Content 1. (**See table 1, Supplemental Digital Content 1**, which displays revision surgery details. **http://links.lww.com/PRSGO/D24**.)

Univariate logistic regression examined each attribute as a potential predictor of secondary procedures. Significant variables ($P < 0.05$) were included in the multivariate logistic regression. Four methods for feature selection for the machine learning model were evaluated: (1) inputting all available preoperative characteristics, (2) inputting variables that were significant on multivariate logistic regression, (3) inputting the top 25 components from principal component analysis of the original dataset, and (4) inputting features that scored above 1 on SelectKBest. The four distinct inputs were used to train a supervised learning model (logistic regression) and an unsupervised learning model (multilayer perceptron). The former was evaluated using fivefold cross validation, and the latter was evaluated using an 80%, 10%, 10% split for training, validation, and testing, respectively.

RESULTS

Of 406 breasts, 185 (45.6%) underwent secondary procedures of any kind. Significant variables on univariate analysis were input into a multivariate analysis. (**See table 2, Supplemental Digital Content 2,** which displays univariate + multivariate analyses. **http://links.lww.com/PRSGO/D25**.)

The performance metrics of the logistic regression and neural network models are shown in Table 1. Of the four feature selection approaches, models trained with variables that were significant on multivariate analysis achieved the highest receiver-operating curve area under the curve (ROC AUC). [**See figure 1, Supplemental Digital Content 3,** which displays ROC AUC for logistic regression models trained on (1) all preoperative variables, (2) variables significant on univariate and multivariate analyses, (3) original dataset after principal component analysis, (4) features selected using SelectKBest in clockwise order. The red dashed line represents ROC AUC for a random chance model. **http://links.lww.com/PRSGO/D26**.] [**See figure 2, Supplemental Digital Content 4**, which displays

Table 1. Machine Learning Model Performance

Machine Learning Model	Input Dataset	ROC AUC	Accuracy	Sensitivity	Specificity
Logistic regression	All variables	0.64	57.9	49.1	65.2
	Features significant on multivariate logistic regression	0.68	60.3	49.1	69.7
	Principal component analysis	0.62	58.4	39.5	56.6
	SelectKBest	0.64	62.1	50.1	71.5
Neural network (multilayer perceptron)	All variables	0.61	63.4	63.2	59.1
	Features significant on multivariate logistic regression	0.74	62.1	84.2	63.6
	Principal component analysis	0.52	51.2	63.2	40.9
	SelectKBest	0.58	61.0	79.1	36.4

ROC AUC for neural network models trained on (1) all preoperative variables, (2) variables significant on univariate and multivariate analyses, (3) original dataset after principal component analysis, (4) features selected using SelectKBest in clockwise order. The blue dashed line represents ROC AUC for a random chance model. **http://links.lww.com/PRSGO/D27**.] The best performing model is publicly available on https://github.com/amychen0815/Revision_Surgery.

DISCUSSION

Machine learning models hold the potential to transform surgical planning by the identification of patients at high risk for complications. In this study, we present our institution's experience developing and testing a novel machine learning model to estimate individual patients' chances of secondary surgery after implant-based reconstruction with excellent sensitivity and specificity.

Among the models evaluated, the neural network model that used variables significant on multivariate analysis achieved the best performance metrics (ROC AUC 0.74, accuracy 0.62), followed by the logistic regression model with the same inputs (ROC AUC 0.68, accuracy 0.60). Generally, models trained with clinically relevant variables had performance superior to that of models using standard dimensionality reduction or feature selection techniques such as principal component analysis or SelectKBest. Incorporating medically significant variables into a predictive model can closely replicate medical professionals' diagnostic reasoning, leading to greater model interpretability. This approach may also capture the underlying pathophysiology and result in predictions better aligned with clinical practice.

This model can be integrated into preoperative consultation to assess an individual's complex interplay of risk factors and comorbidities. For example, take a patient with recently diagnosed breast cancer. She is otherwise healthy, has never smoked, and has a nipple-inframammary fold distance of 4 centimeters. The surgeon proceeds with textured tissue expanders and an initial intraoperative tissue expander filling volume of 500 mL. Using our model, her predicted likelihood of requiring secondary surgery is approximately 38.5%. If instead she has a smoking history, a nipple-inframammary fold measurement of 9 cm, and the surgeon decides to use a smooth tissue expander with a vertical radial incision, her odds of requiring revision surgery increases to 96.4%. For patients at heightened risk, physicians may recommend risk-reducing lifestyle modifications or suggest alternative modalities such as autologous reconstruction.

Personalized risk prediction is particularly important in the field of plastic surgery, where outcomes can be highly surgeon or institution dependent. Our model, trained on a single surgeon's data, may not be generalizable to all surgeons, but other physicians may input their own datasets into the model and produce tailored outcome predictions for their respective patient populations. As a pilot study, there are a few limitations. Our model was trained on a retrospective dataset, so causation cannot be established between the variables analyzed. Furthermore, there is a risk of nonsensical associations from multiple comparisons. We present our pilot study developing a machine learning model with the hopes of inspiring widespread integration and adoption of artificial intelligence for risk prediction in a variety of plastic surgery procedures.

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DISCLOSURE

The authors have no financial interest to declare in relation to the content of this article.

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