Machine learning modeling for predicting hospital readmission following lumbar laminectomy

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OBJECTIVE Hospital readmission contributes substantial costs to the healthcare system. The purpose of this investigation was to create a predictive machine learning model to identify lumbar laminectomy patients at risk for postoperative hospital readmission.

METHODS Patients who had undergone a lumbar laminectomy procedure in the period from 2011 to 2014 were isolated from the American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP) database. Demographic characteristics and clinical factors, including complications, comorbidities, length of stay, age, and body mass index, were analyzed in relation to whether or not the patients had been readmitted to the hospital within 30 days after their procedure by utilizing independent-samples t-tests. Supervised gradient boosting machine learning was then used to create two models to predict readmission—one with all collected patient variables and one with only the variables known prior to hospital discharge.

RESULTS A total of 26,869 patients were evaluated, 5.59% (1501 patients) of whom had an unplanned readmission to the hospital within 30 days of their procedure. Readmitted patients were older and had a greater number of complications and comorbidities, longer operative time, longer hospital stay, higher BMI, and higher work relative value unit (RVU) operation score ($p < 0.01$). They also had a worse health status prior to surgery ($p < 0.01$) and were more likely to be sent to a skilled discharge destination postoperatively ($p < 0.01$). The model with all patient variables accurately identified 49.6% of readmissions with an overall accuracy of 95.33% (area under the curve [AUC] = 0.8059), with postdischarge complications and comorbidities as the most important predictors. The predictive model built with only clinical information known pre-discharge identified 40.5% of readmitted patients with an accuracy of 79.55% (AUC = 0.6901), with discharge destination, comorbidities, and American Society of Anesthesiologists (ASA) classification as the most influential factors in identifying readmitted patients.

CONCLUSIONS In this study, the authors analyzed hospital readmissions following laminectomy and developed predictive models to identify readmitted patients with an accuracy of over 95% using all variables and over 79% when using only pre-discharge variables. Using only the variables available pre-discharge, the authors created a model capable of predicting 40% of the readmitted patients. This study provides data that will assist in the development of predictive models for readmission and the creation of interventions to prevent readmission in high-risk patients.

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KEYWORDS hospital readmission; spine surgery; machine learning; predictive model; lumbar; diagnostic technique

IN 2011 an estimated 3.3 million people in the US were readmitted to the hospital within 30 days of their discharge, leading to \$41.3 billion in potentially preventable healthcare expenditures.¹⁵ Patients over the age of 65 years and insured under Medicare had the highest readmission rates, making up 55.9% of readmissions and

accounting for 58.2% of readmission costs.¹⁵ Additionally, readmitted patients had substantially reduced health-related quality of life measures, including both physical and psychosocial components.^{28,30}

For spine surgery, reported 30-day readmission rates vary from 4.2% to 7.4%.⁸ A majority of these readmissions

ABBREVIATIONS ASA = American Society of Anesthesiologists; AUC = area under the receiver operating characteristic curve; BMI = body mass index; GBM = gradient boosting machine; LOS = length of stay; RVU = relative value unit; SMOTE = Synthetic Minority Oversampling Technique.

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are unplanned and attributable to postdischarge complications, whether medical or surgical.² More than half of these cases require additional surgery and result in longer hospital stays. These effects can translate into substantially increased costs for the healthcare system.^{24,31}

Because of its high rates and costs, readmission has gained substantial attention in recent years and is increasingly discussed as an indicator of a hospital's inpatient quality of care and discharge procedures.^{6,22,34} Therefore, in 2012 the Centers for Medicare and Medicaid Services (CMS) put into effect the Hospital Readmissions Reduction Program (HRRP), which incentivizes hospitals to bring down their readmission rates by reducing Medicare reimbursement payments to those with high rates.²⁵ In 2017, of the approximately 3760 institutions participating in the program, 2597 of them, or 69%, were penalized for high readmission numbers.^{3,40}

Driven by a consumer push toward a higher quality of care and programs such as the HRRP, there has been increasing interest and research in reducing readmissions, especially those identified as preventable.^{4,19,27} By recent estimates, preventable readmissions make up as much as 20% of these cases and cost up to \$17 billion annually.³⁷ There are also ongoing efforts to better understand and identify the factors that lead to readmission, which can lead to the development of more effective interventions.^{5,11,18} A recent investigation found that the most common causes for readmission after spine surgery included infection at the surgical site and pain.⁸

The objective of the present study was to analyze factors associated with 30-day hospital readmission following lumbar laminectomy and to create machine learning-based models to predict these readmissions.³⁸ We hypothesized that the factors most influential in forecasting readmission would be postoperative complications and preoperative patient health status, such as preexisting health conditions and dependency levels.

Methods

Patient Selection

Data were obtained from the American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP) database. This annually released data set collects de-identified demographic and clinical data from patient medical charts in hospitals across the country. Patients are also tracked for 30 days after their operation to collect additional information about complications.¹ For this study, those who had undergone a laminectomy procedure (Current Procedural Terminology [CPT] codes 63001–63017, 63045–63048)²⁹ between 2011 and 2014 were identified. The readmission status for each patient, whether or not they had been readmitted to the hospital in the 30 days after the operation, was obtained.

Independent-Samples t-Tests

Independent-samples t-tests were performed to examine differences between those who had been readmitted and those who had not (statistical cutoff: $p < 0.05$). Fourteen variables describing patient and operation characteristics were examined: age, operation time, total hospital

length of stay (LOS), postoperative LOS, body mass index (BMI), dependency, number of in-hospital complications, number of postdischarge complications, total number of complications, specific type of discharge destination postoperation, skilled discharge destination postoperation, American Society of Anesthesiologists (ASA) classification, work relative value units (RVUs) for the hospital stay, and number of comorbidities. Listwise deletion was utilized for missing data. Variables with more than 2.5% missing data were excluded in order to preserve statistical rigor.

Twenty-one common postsurgical complications and 36 comorbidities were evaluated for each patient (Table 1).²¹ Specific discharge destination is where the patients were discharged to, ranked by skill. A higher specific discharge destination score corresponds to a more skilled destination: home (score = 1), facility that is home (score = 2), unskilled facility that is not home (score = 3), rehab (score = 4), skilled care (score = 5), and separate acute care (score = 6). The skilled destination variable was coded as either 0 to indicate a nonskilled destination or 1 to indicate a skilled destination. Lastly, a higher dependency score corresponds to a lower functional health status prior to surgery, from independent (score = 1) to totally dependent (score = 3). Data were analyzed using SPSS version 24 (IBM Corp.).

Modeling Readmission With Supervised Machine Learning

Machine learning algorithms to predict hospital readmission utilized R version 3.4.1 (R Foundation for Statistical Computing) and MATLAB version R2017a (MathWorks). The 14 characteristic variables were assigned as features in the model, and the readmission status was assigned as a binary outcome variable. Data were randomly partitioned into training (85%) and testing (15%) data sets. A Synthetic Minority Oversampling Technique (SMOTE) was subsequently applied to handle the class imbalance in the data set as only 5.59% of patients were readmitted. SMOTE is a widely used sampling-based algorithm that uses proportional oversampling and undersampling to create more balanced data and improve a model's predictive ability.¹⁰ Algorithms were performed both with and without SMOTE using the same testing data set for validation.

After the data set was prepared, the package *rpart* (<https://cran.r-project.org/web/packages/rpart/rpart.pdf>) was used on the training data to create decision trees, which are nonparametric supervised learning methods for classification problems. The decision tree was pruned by minimizing the cross-validated error to reduce complexity and prevent overfitting of the data.⁴¹ It was then used to understand how each feature impacted readmission and to identify the most important features out of the 14.

Lastly, because readmission is a binary classification outcome, supervised gradient boosting machine (GBM) learning was used to create a prediction model. In this situation, gradient boosting is preferable to other types of ensemble machine learning, such as random forests. While the random forest technique consists of averaging all of the generated models, a GBM adds each new model to the others sequentially, iteratively improving the ensemble and more accurately estimating the outcome.²⁶ Friedman's

gradient boosting algorithm was used, where $L(y_i, f)$ is the loss function, $h(x_i; a_m)$ is the base learner, and σ_m is the optimized step size to add to the previous function $f_{m-1}(x)$.^{13,26}

$$\sigma_m = \arg \min_{\sigma} \sum_{i=1}^N L(y_i, f_{m-1}(x_i) + \sigma h(x_i; a_m)) \quad [\text{Eq. 1}]^{13}$$

$$f_m(x) = f_{m-1}(x) + \sigma_m h(x; a_m) \quad [\text{Eq. 2}]^{13}$$

For this study, a GBM with three repeats of a 10-fold cross-validation technique was utilized, with each repeat consisting of 150 iterations to minimize the value of the loss function. Two different models were created: one with all the variables and one with only the pre-discharge variables. The algorithm was created based on the training data and then validated with the testing data set. The performance of each model in the test was evaluated by its accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC). Further, relative importance values for each variable in the models were calculated, and partial dependency plots portraying the marginal effect of the variables on readmission were plotted (<http://math.furman.edu/~dcs/courses/math47/R/library/randomForest/html/partialPlot.html>).

Results

In total, 26,869 patients were analyzed, 5.59% (1501 patients) of whom had been readmitted within 30 days postoperatively. Readmitted patients and non-readmitted patients had statistically different values ($p < 0.001$) for all 14 examined variables (Table 2). Those who had been readmitted were significantly older (64.668 vs 62.303, $p < 0.001$) and had a significantly longer operation time (158.584 vs 140.349, $p < 0.001$), higher RVU procedure score (35.512 vs 31.646, $p < 0.001$), longer total (4.618 vs 3.197, $p < 0.001$) and postoperation (3.861 vs 2.812, $p < 0.001$) hospital LOS, higher BMI (31.726 vs 30.957, $p < 0.001$), greater number of complications (in-hospital: 0.170 vs 0.097, $p < 0.001$; postdischarge: 0.684 vs 0.025, $p < 0.001$; and total: 0.783 vs 0.117, $p < 0.001$), and greater number of comorbidities (1.558 vs 1.212, $p < 0.001$).

Not all patients with recorded postdischarge complications were readmitted; 57.5% (331/576) of those with one, 55.7% (205/368) of those with two, and 82.0% (73/89) of those with three or more postdischarge complications were readmitted. Overall, 58.9% (609/1033) of the patients with identified postdischarge surgical complications were readmitted. Further, readmitted patients also had greater dependency (lower functional status) prior to surgery (1.094 vs 1.036, $p < 0.001$) and were ranked worse on the ASA classification scale (2.741 vs 2.507, $p < 0.001$). Lastly, patients who had been readmitted were more likely to be discharged to a skilled destination (0.301 vs 0.152, $p < 0.001$) such as a skilled nursing home.

Models Containing All Variables: Single Decision Tree

The initial decision tree (Fig. 1) showed that three variables were predictive of readmission (in order of descending predictive power): postdischarge complications, any complications, and BMI. From this tree, three groups of patients were more likely to be readmitted than not. Fifty-

TABLE 1. List of examined complications and comorbidities*

No.	Complication	Comorbidity
1	Superficial incisional SSI	Diabetes
2	Deep incisional SSI	Smoking
3	Organ/space SSI	High alcohol use
4	Wound disruption	Ventilator dependent
5	Pneumonia	History of severe COPD
6	Unplanned intubation	Current pneumonia
7	Pulmonary embolism	Ascites
8	On ventilator for >48 hrs	Esophageal varices
9	Progressive renal insufficiency	Congestive heart failure (in the 30 days prior to surgery)
10	Acute renal failure	Myocardial infarction (in the 6 mos prior to surgery)
11	Urinary tract infection	Previous percutaneous coronary intervention
12	Stroke/CVA	Previous cardiac surgery
13	Coma (>24 hrs)	Angina (in the month prior to surgery)
14	Peripheral nerve injury	Hypertension requiring medicine
15	Cardiac arrest requiring CPR	History of revascularization/amputation for peripheral vascular disease
16	Myocardial infarction	Rest pain/gangrene
17	Bleeding transfusion	Acute renal failure
18	Failure of graft, prosthesis, or flap	Currently on dialysis
19	Thrombophlebitis/DVT	Impaired sensorium
20	Sepsis occurrence	In coma for >24 hrs
21	Septic shock occurrence	Hemiplegia
22		History of transient ischemic attacks
23		CVA or stroke w/ or w/o neurological deficit
24		CNS tumor
25		Paraplegia
26		Quadriplegia
27		Disseminated cancer
28		Open wound infection prior to surgery
29		Steroid use for chronic condition
30		Weight loss (>10% loss in the 6 mos prior to surgery)
31		Bleeding disorder
32		Preop transfusion of RBCs
33		Chemotherapy (in the 30 days prior to surgery)
34		Radiotherapy (in the 90 days prior to surgery)
35		Systemic sepsis
36		Previous operation (in the 30 days prior to surgery)

CNS = central nervous system; COPD = chronic obstructive pulmonary disease; CPR = cardiopulmonary resuscitation; CVA = cerebrovascular accident; DVT = deep vein thrombosis; RBC = red blood cell; SSI = surgical site infection.

* Lawson et al., 2013.

TABLE 2. Variable differences between readmitted and non-readmitted patients

Variable	Readmitted Patients	Non-Readmitted Patients	Mean Difference	p Value	95% CI of the Difference	
					Upper	Lower
Age	64.668	62.303	2.365	<0.001	3.072	1.659
BMI	31.726	30.957	0.769	<0.001	1.149	0.389
Dependency	1.094	1.036	0.058	<0.001	0.069	0.047
ASA classification	2.741	2.507	0.234	<0.001	0.267	0.202
Operation time	158.584	140.349	18.235	<0.001	22.802	13.669
RVU score	35.512	31.646	3.866	<0.001	5.044	2.688
Total hospital LOS	4.618	3.197	1.421	<0.001	1.745	1.097
Postoperation LOS	3.861	2.812	1.048	<0.001	1.412	0.684
Skilled discharge destination	0.301	0.152	0.149	<0.001	0.168	0.129
Specific discharge destination	2.058	1.546	0.512	<0.001	0.581	0.443
Comorbidities	1.558	1.212	0.346	<0.001	0.403	0.290
Total complications	0.783	0.117	0.666	<0.001	0.691	0.641
In-hospital complications	0.170	0.097	0.073	<0.001	0.093	0.052
Postdischarge complications	0.684	0.025	0.659	<0.001	0.675	0.642

nine percent of the people with any postdischarge complication were readmitted. Seventy-seven percent of patients who had a postdischarge complication and at least two complications in total were readmitted. Fifty-eight percent of those with a postdischarge complication and a BMI > 25 kg/m² were readmitted.

Though only 3% of those without postdischarge complications were readmitted, they composed 59.2% of all those who were readmitted. Of these patients, 41.2% were determined to have a condition unrelated to the surgical procedure and instead were readmitted for other clinical reasons. This group was significantly ($p < 0.05$) older, had

FIG. 1. Decision tree to predict readmission based on patient clinical and demographic factors. Figure is available in color online only.

FIG. 2. Variable influence scores in full GBM readmission predictive model. Figure is available in color online only.

a greater number of comorbidities, and had a higher ASA classification than those who were readmitted with conditions attributable to their operation. The remaining 58.7% had other complications related to the procedure, most commonly “acute postoperative pain,” which accounted for 13% of the other readmissions.

Models Containing All Variables: GBM Learning

The GBM model to identify readmission was 95.33%

accurate (95% CI 94.64%–95.96%) with an AUC of 0.8059. The specificity was 0.9808 and the sensitivity was 0.4955. The most important variable in the model was postdischarge complications, followed by comorbidities, discharge destination, ASA classification, and total number of complications. The relative influence scores of the other variables were less than 1, signifying that they only minimally impacted the model. Notably, in-hospital complications were the least important factors in identifying

FIG. 3. Partial dependency plots of all variables' marginal effects on readmission.

FIG. 4. Variable influence scores in predischARGE GBM readmission predictive model. Figure is available in color online only.

readmission (Fig. 2). The partial dependency plots for the model (Fig. 3) similarly showed that the presence of post-discharge complications and the number of comorbidities have the greatest effects on readmission. Interestingly, only patients with three to five comorbidities had a considerably increased readmission risk. Lower and higher comorbidity numbers outside of this range were not associated with more readmissions.

Model Containing Only PredischARGE Variables: GBM Learning

The GBM model to predict readmission with only information known prior to readmission had an accuracy of 79.55% (95% CI 78.27%–80.78%) and an AUC of 0.6901. The sensitivity of the model was 40.45% and the specificity was 81.81%. The most important variables in forecasting readmission were discharge destination, comorbidities, ASA classification, and total hospital LOS. The other variables had little effect on the model. As in the other model, the presence of in-hospital complications had the least influence on predicting readmission (Fig. 4).

The partial dependency plots with the predischARGE variables (Fig. 5) demonstrated that ASA class, number of comorbidities, and type of discharge destination had the greatest effects on readmission rates. Patients with ASA scores that indicate mild (ASA class 2) or severe (ASA class 3) systemic disease had higher readmission rates than those with no systemic disease or with life-threatening systemic disease. The presence of at least one comorbidity, but especially between three and five comorbidities, increased readmission occurrence. Lastly, discharge to home, a skilled care facility, or separate acute care was associated with less readmission than discharge to rehab, an unskilled facility, or a facility that was previously home.

Discussion

In this study we identified factors associated with hospital readmission following laminectomy and created a predictive model capable of detecting readmitted patients with the GBM model being 95.33% accurate with an AUC of 0.8059, indicating strong discriminative ability.¹⁶ It was

also highly specific, signifying that any negative readmission projection has a high probability of accuracy; 97.04% of the negative predictions were accurate, higher than the 94.54% no-readmission rate and indicating potential clinical usefulness.

Overall, the model with all variables identified approximately half of the readmitted patients, and consistent with findings in previous studies, the most significant variable was the number of common surgical postdischarge complications.^{21,32} A little more than half of all patients with post-discharge complications were readmitted, with the probability of readmission increasing to over 80% only when the number of postdischarge complications was three or greater. Taken together, these data indicate that the model has predictive ability in forecasting readmission if patients are followed after initial discharge and that the presence of postdischarge complications does not guarantee readmission.

The GBM model that utilized only predischARGE information was 79.55% accurate with a sensitivity of 40.5% and an AUC of 0.6901, indicating fair predictive ability. Though less accurate than the first model, the predischARGE GBM model was able to predict approximately 40% of future readmissions with no information about postdischarge complications. As previous studies have noted, reducing readmission by even a few percentage points would have a considerable impact on the economic burden.³²

A binary logistic regression including the same variables as the full GBM model yielded a Cox-Snell R^2 value of 0.096 and was able to identify 25.3% of readmissions, which is substantially lower than the 49.6% identified with GBM. A similar regression model including only the variables in the predischARGE GBM model yielded a Cox-Snell R^2 value of 0.015 and was able to identify 0% of readmissions, which again is considerably lower than the 40.5% identified with GBM. Taken together, these data indicate that the machine learning model was able to predict hospital readmission more accurately than standard regression statistics.

The cause of readmission varied widely among the patient population. Sixty percent of readmission cases had no postdischarge surgical complications recorded in the

FIG. 5. Partial dependency plots of predischarge variables' marginal effects on readmission.

NSQIP. Among all patients, 24% were readmitted due to other health conditions unrelated to the laminectomy, and another 36% had various diagnoses for readmission. However, more than 40% of the readmitted patients, or just those with postdischarge complications, were identified by the algorithm. Thus, the model was able to identify patient factors that increased readmission risk not related to the common complications and that existed throughout the population. Further research utilizing data with a greater breadth of predictive characteristics is warranted.

The most important variable for predicting readmission a priori was discharge destination. Readmitted patients were significantly more likely to go to a skilled destination after the operation. Compared to those discharged home after surgery, patients who are discharged to professional facilities tend to have worse health overall; this is supported by the fact that comorbidities and ASA classification are the next most important predictors of readmission. Thus, future hospital readmission seems largely linked to health status prior to surgery, which can be used to identify high-risk patients. It is also noteworthy that both models identified in-hospital complications as the least important variable in predicting readmission. This suggests that spine surgeons and their consulting physician services are largely able to effectively manage in-hospital complications without affecting readmission risk.

In general, black box machine learning methods are typically more accurate for numerous applications because they do not make the assumptions that other methods, such as logistic regression, make when analyzing data.^{9,12,42} Further, comparisons of different methodologies in predicting health outcomes have often revealed that black box learning methods outperform more traditional statistical techniques such as regression.^{33,39} Consequently, machine learning methods are becoming increasingly useful and relevant across the healthcare industry and will likely become an important part of risk management, diagnosis,

and the management of the everyday practice of medicine going forward.^{7,23} As public health surveillance continues to evolve, the granularity of machine learning models can also improve with higher-quality and more specific patient information, enhancing the predictive power of the models.

One systematic review examined 9 different predictive readmission models that used retrospective US health data and reported an AUC value; of these studies, none had as high an AUC or discriminative power to predict readmission as the model in our investigation.¹⁷ Other risk indices for readmission, such as the LACE score, had a slightly lower AUC than the predischarge model presented in this study.³⁵ Another study compared 14 various machine learning and regression techniques in predicting readmission. The model with the best discriminative power was a black box technique, and its AUC was also slightly lower than the AUC for the GBM predischarge model.¹⁴

This study has several potential limitations. Most algorithms work best if data are evenly split between the various outcomes and many are not accurate with rare events.³⁶ However, readmission data for the most part are imbalanced and have many more cases of those who were not readmitted. This makes readmission difficult to model using traditional machine learning; differentially sampling the cases may result in overfitting. Moreover, GBM models themselves are prone to overfitting the data if not properly tested.²⁰ Note, we did employ pruning and used a testing data set in an effort to reduce the impact of overfitting and certify our model. However, future studies must gather more data to validate the algorithm before it can be applied. Once validated, the algorithm can be converted to a readmission risk scoring tool that can be easily utilized in the clinical setting.

Conclusions

This investigation demonstrated that readmitted pa-

tients differ from non-readmitted patients in most factors and that readmission can be predicted accurately with only predischarge information. A substantial number of readmissions following laminectomy may not be attributable to the procedure itself, but rather to other patient-level characteristics, including comorbidities and discharge destination. Further, machine learning methods predict readmission more accurately than regression statistics. Machine learning predictive models in the clinical setting can identify patients who are at higher risk for readmission in order to develop more targeted interventions to prevent unnecessary readmission following laminectomy.

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Conception and design: Daniels, Kalagara, Eltorai. Analysis and interpretation of data: Kalagara. Drafting the article: Kalagara, Eltorai. Critically revising the article: all authors. Reviewed submitted version of manuscript: all authors. Statistical analysis: Kalagara, Durand. Administrative/technical/material support: Daniels, Eltorai. Study supervision: all authors.

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