The American Surgeon™
2023, Vol. 89(12) 5702–5710

DOI: 10.1177/00031348231173981
journals.sagepub.com/home/asu
Sage

Prediction of Ureteral Injury During Colorectal Surgery Using Machine Learning

Kevin A. Chen, MD[1], Chinmaya U. Joisa, BS[2], Jonathan M. Stem, MD[1], Jose G. Guillem, MD[1], Shawn M. Gomez, EngScD[2], and Muneera R. Kapadia, MD, MME[1]

Abstract

Background: Ureteral injury (UI) is a rare but devastating complication during colorectal surgery. Ureteral stents may reduce UI but carry risks themselves. Risk predictors for UI could help target the use of stents, but previous efforts have relied on logistic regression (LR), shown moderate accuracy, and used intraoperative variables. We sought to use an emerging approach in predictive analytics, machine learning, to create a model for UI.

Methods: Patients who underwent colorectal surgery were identified in the National Surgical Quality Improvement Program (NSQIP) database. Patients were split into training, validation, and test sets. The primary outcome was UI. Three machine learning approaches were tested including random forest (RF), gradient boosting (XGB), and neural networks (NN), and compared with traditional LR. Model performance was assessed using area under the curve (AUROC).

Results: The data set included 262,923 patients, of whom 1519 (.578%) experienced UI. Of the modeling techniques, XGB performed the best, with an AUROC score of .774 (95% CI .742-.807) compared with .698 (95% CI .664-.733) for LR. Random forest and NN performed similarly with scores of .738 and .763, respectively. Type of procedure, work RVUs, indication for surgery, and mechanical bowel prep showed the strongest influence on model predictions.

Conclusions: Machine learning-based models significantly outperformed LR and previous models and showed high accuracy in predicting UI during colorectal surgery. With proper validation, they could be used to support decision making regarding the placement of ureteral stents preoperatively.

Keywords
machine learning, artificial intelligence, ureteral injury, colorectal surgery

Key Takeaways

- Machine learning-based models significantly outperformed logistic regression in the prediction of ureteral injury during colorectal surgery.
- With proper validation, these machine learning models could augment surgeon judgment by identifying patients at highest risk of UI for consideration of ureteral stent placement.

Introduction

Ureteral injury (UI) is a rare but devastating complication of colorectal surgery, occurring in .3-.6% of cases.[1,2] In addition to the injury, UI is associated with higher morbidity, mortality, length of stay, and hospital charges.[1] Identifying the ureter is a key step in most colorectal operations, and ureteral stents may help surgeons rapidly and safely identify the ureter in cases of increased complexity. Ureteral stent placement may be associated with a decreased rate of UI, but stent placement itself carries risks, including hematuria, urinary tract infection, acute kidney injury, and stent migration.[3,4]

[1]Department of Surgery, University of North Carolina at Chapel Hill, NC, USA
[2]Joint Department of Biomedical Engineering, University of North Carolina at Chapel Hill, NC, USA

Corresponding Author:
Muneera R. Kapadia, MD, MME, Division of Gastrointestinal Surgery, Department of Surgery, University of North Carolina at Chapel Hill, 100 Manning Drive, Burnett Womack Building, Suite 4038, Chapel Hill, NC 27599, USA.
Email: muneera_kapadia@med.unc.edu

A predictive model to identify patients at highest risk of UI would be helpful in selecting patients who would benefit most from ureteral stents. Previous efforts have created a predictive model based on logistic regression (LR) for this outcome, but they showed limited accuracy and required intraoperative information.[1] This limits the usefulness of these models, as ureteral stent placement occurs prior to surgery and intraoperative information is not yet known. Machine learning is an emerging technique within data science that uses computational methods to find nonlinear patterns in large data sets. It has been successfully applied to the prediction of procedure-specific outcomes, such as pancreatic fistula and complexity of abdominal wall reconstruction.[5-7]

We sought to use machine learning to predict UI during colorectal surgery and create a tool which could be used to guide ureteral stent placement. Our hypothesis was that machine learning methods applied to multi-institutional data from the National Surgical Quality Improvement Program (NSQIP) database would outperform previous approaches and result in a more accurate model.

Methods

Data

Study exemption and waiver of informed consent were obtained from the University of North Carolina Institutional Review Board. We used data from the NSQIP database, including the proctectomy and colectomy procedure-targeted data sets. NSQIP collects data from more than 700 participating hospitals using trained surgical reviewers, with reliability ensured through rigorous training and reliability audits.[8] We used all available years, which included 2012 to 2019 for colectomy and 2016 to 2019 for proctectomy. Data from 2019 were held out as an external test set, as it was the most recent year available and would most closely resemble current patients. Data from 2012 to 2018 were split into training and validation sets in an 80/20 ratio with 5-fold cross-validation. These data were used for model training, adjusting model settings (hyperparameters), and ensuring model generalizability prior to evaluation on the test. This work is reported in accordance with the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) checklist.

Outcomes and Variables

Using methods described by Coakley et al, we identified UI by searching the CPT codes for concurrent procedures for codes indicating repair of ureters.[2] These included CPT codes 50740, 50750, 50760, 50770, 50780, 50783, 50785, 50800, 50810, 50815, 50820, 50825, 50840, 50845, 50860, 50900, 50947, 50948, 50949, 52334, and 50040. We also searched these CPT codes for "return to OR" and ICD codes for "indications for return to OR" indicating UI (ICD9: 867.2, 867.3; ICD10: S37). For model development, we excluded cases where prophylactic ureteral stents were placed (CPT code 52005).[4] Other variables were preprocessed in accordance with prior work, with missing categorical variables imputed as a unique "missing" class and numerical variables imputed as the median.[9] All available preoperative variables were included in the models, with a full list available in Table 1.

Modeling

We applied various machine learning approaches including random forest (RF), gradient boosting (XGB), and deep neural networks (NNs). We compared these techniques with LR. Random forest and XGB are based on combining decision trees, while NN processes data through nonlinear functions that are adjusted with training.[9] Hyperparameters were tuned for each algorithm using Bayesian optimization from the scikit-optimize library. This algorithm explores a wide range of hyperparameters and uses previous results to guide a targeted search for the highest performing set. For RF and XGB, hyperparameters included the number of trees, the maximum tree depth, the minimum samples per split, the number of features considered per split, and the subsample of features considered. For NN, hyperparameters included the number of neurons, the number of layers, the percentage of dropout used per layer, and the learning rate.

Evaluation

We evaluated each model using area under the receiver operating characteristic curve (AUROC) and area under the precision-recall curve (AUPRC). Area under the receiver operating characteristic curve is based on a plot of sensitivity vs 1 – specificity and represents a model's ability to distinguish positive from negative cases. Area under the receiver operating characteristic curve ranges from .5 to 1, with .5 representing random guessing and 1 representing perfect classification. The DeLong test was used to compare AUROC, with significance set at $P < .05$.[10] Area under the precision-recall curve is based on a plot of sensitivity vs positive predictive value and represents a model's ability to identify all positive cases without identifying negative cases. Area under the precision-recall curve ranges from the rate of the positive class (ie, the rate of UI) to 1 (representing perfect sensitivity). We also calculated sensitivity, specificity, positive predictive value, and negative predictive value. Model performance was also analyzed among patients who had ureteral stents placed. We used Shapley additive explanations to identify which variables had the strongest impact on model predictions.[11] LR, RF, and XGB were

Table 1. Included Variables for the Prediction of Ureteral Injury.

Variable	Category	Missing	No Injury, *n* (%)	Ureter Injury *n* (%)	*P*-Value
Age, mean (SD)		0	61.6 (15.5)	60.0 (13.8)	<.001
Sex	Female	0	136502 (52.2)	697 (45.9)	0.334
	Male		124899 (47.8)	822 (54.1)	
	Non-binary		3 (0.0)	0 (0.0)	
Height (m), mean (SD)		5162	1.7 (.1)	1.7 (.1)	.050
Weight		3071	80.0 (21.5)	80.3 (22.2)	.617
BMI		5478	28.4 (6.7)	28.7 (7.0)	.105
Race/ethnicity	Non-Hispanic White	0	183274 (70.1)	1024 (67.4)	.027
	Non-Hispanic Black		23208 (8.9)	154 (10.1)	
	Hispanic		13159 (5.0)	97 (6.4)	
	Asian		8050 (3.1)	53 (3.5)	
	American Indian or Alaskan native		948 (.4)	4 (.3)	
	Native Hawaiian or Pacific Islander		542 (.2)	4 (.3)	
	Unknown/not reported		32223 (12.3)	183 (12.0)	
Procedure	Abdominoperineal resection	0	3353 (1.3)	51 (3.4)	<.001
	Colectomy, combined transanal approach		366 (.1)	3 (.2)	
	L-sided colectomy		36840 (14.1)	452 (29.8)	
	Low anterior resection		4143 (1.6)	35 (2.3)	
	Laparoscopic L-sided colectomy		42971 (16.4)	374 (24.6)	
	Laparoscopic LAR		2770 (1.1)	12 (.8)	
	Laparoscopic R-sided colectomy		34869 (13.3)	48 (3.2)	
	Laparoscopic partial colectomy		50404 (19.3)	161 (10.6)	
	Laparoscopic proctocolectomy		2049 (.8)	7 (.5)	
	Laparoscopic rectopexy		549 (.2)		
	Laparoscopic total colectomy		6617 (2.5)	18 (1.2)	
	Partial colectomy		39998 (15.3)	191 (12.6)	
	Pelvic exenteration		360 (.1)	46 (3.0)	
	Proctectomy, perineal approach		2180 (.8)	4 (.3)	
	Proctectomy, other approach		109 (.0)	2 (.1)	
	Proctocolectomy		876 (.3)	9 (.6)	
	R-sided colectomy		25637 (9.8)	79 (5.2)	
	Total colectomy		7313 (2.8)	27 (1.8)	
Indication	Acute diverticulitis	2391	20202 (7.8)	159 (10.8)	<.001
	Anal cancer		388 (.1)	3 (.2)	
	Bleeding		1772 (.7)	5 (.3)	
	Chronic diverticular disease		32433 (12.5)	303 (20.5)	
	Colon cancer		86943 (33.6)	432 (29.3)	
	Colon cancer w/obstruction		11510 (4.4)	44 (3.0)	
	Crohn's disease		14997 (5.8)	52 (3.5)	
	Enterocolitis (eg, C. difficile)		1448 (.6)	1 (.1)	
	Non-malignant polyp		20520 (7.9)	22 (1.5)	
	Other		43082 (16.6)	328 (22.2)	
	Rectal cancer		7894 (3.0)	109 (7.4)	
	Rectal prolapse		2448 (.9)	0 (.0)	
	Ulcerative colitis		8349 (3.2)	15 (1.0)	
	Volvulus		7071 (2.7)	2 (.1)	
Antibiotic bowel prep	Yes	44166	124294 (57.1)	627 (56.6)	.751
	No		93355 (42.9)	481 (43.4)	
Mechanical bowel prep	Yes	46861	90907 (42.3)	439 (41.6)	.683
	No		124100 (57.7)	616 (58.4)	
Emergent indication	Bleeding	0	1767 (.7)	1763 (.7)	<.001
	Obstruction		10375 (4.0)	44 (2.9)	
	Perforation		18115 (6.9)	27 (1.8)	
	Not emergent		223210 (85.4)	1431 (94.2)	
	Other		5295 (2.0)	12 (.8)	

(Continued)

Table 1. Continued

Variable	Category	Missing	No Injury, *n* (%)	Ureter Injury *n* (%)	*P*-Value
Approach	Open (planned)	86	95084 (36.4)	709 (46.7)	<.001
	Laparoscopic		125413 (48.0)	574 (37.8)	
	Laparoscopic w/unplanned conversion to open		16409 (6.3)	130 (8.6)	
	Robotic		24016 (9.2)	103 (6.8)	
	Other		397 (.2)	2 (.1)	
Transfer status	From acute care hospital inpatient	248	8020 (3.1)	25 (1.6)	<.001
	Not transferred (admitted from home)		241939 (92.6)	1458 (96.0)	
	Nursing home—chronic care—intermediate care		3291 (1.3)	11 (.7)	
	Outside emergency department		6804 (2.6)	19 (1.3)	
	Transfer from other		1103 (.4)	5 (.3)	
Diabetes	Insulin dependent	0	13863 (5.3)	67 (4.4)	.204
	No diabetes		221574 (84.8)	1310 (86.2)	
	Medication only		25967 (9.9)	142 (9.3)	
Smoking	Yes	0	43201 (16.5)	311 (20.5)	<.001
Dyspnea	At rest	0	1548 (.6)	3 (.2)	.071
	Moderate exertion		16223 (6.2)	84 (5.5)	
	No		243633 (93.2)	1432 (94.3)	
Functional status	Independent	0	251671 (96.7)	1483 (97.8)	.040
	Partially dependent		6975 (2.7)	27 (1.8)	
	Totally dependent		1740 (.7)	6 (.4)	
COPD	Yes	0	14301 (5.5)	60 (3.9)	.011
Ascites	Yes	0	2215 (.8)	9 (.6)	.347
Heart failure	Yes	0	3394 (1.3)	10 (.7)	.037
Hypertension	Yes	0	123636 (47.3)	663 (43.6)	.005
Acute renal failure	Yes	0	1746 (.7)	3 (.2)	.037
Dialysis	Yes	0	3062 (1.2)	7 (.5)	.014
Disseminated cancer	Yes	0	16892 (6.5)	191 (12.6)	<.001
Steroid use	Yes	19527	16888 (7.0)	68 (5.1)	.007
Weight loss	Yes	0	13038 (5.0)	96 (6.3)	.020
Bleeding disorder	Yes	0	12318 (4.7)	44 (2.9)	.001
Preoperative transfusion requirement	Yes	0	7569 (2.9)	31 (2.0)	.057
Preoperative sepsis	None	0	230211 (88.1)	1421 (93.5)	<.001
	SIRS		8476 (3.2)	38 (2.5)	
	Sepsis		16367 (6.3)	53 (3.5)	
	Septic shock		6350 (2.4)	7 (.5)	
ASA classification	1-No disturbance	0	5382 (2.1)	19 (1.3)	<.001
	2-Mild disturbance		101812 (38.9)	591 (38.9)	
	3-Severe disturbance		128248 (49.1)	814 (53.6)	
	4-Life threatening		23844 (9.1)	88 (5.8)	
	5-Moribund		1821 (.7)	7 (.5)	
	None assigned		297 (.1)	0 (.0)	
Superficial SSI PATOS	Yes	0	473 (.2)	4 (.3)	.361
Deep SSI PATOS	Yes	0	342 (.1)	3 (.2)	.457
Organ-space SSI PATOS	Yes	0	5435 (2.1)	38 (2.5)	.289
Pneumonia PATOS	Yes	0	1320 (.5)		.009
Ventilator-dependent PATOS	Yes	0	1944 (.7)	2 (.1)	.009
Urinary tract infection PATOS	Yes	0	787 (.3)	22 (1.4)	<.001
Sepsis PATOS	Yes	0	6931 (2.7)	40 (2.6)	1.000
Septic shock PATOS	Yes	0	6735 (2.6)	14 (.9)	<.001
Work RVU, mean (SD)		0	26.8 (4.3)	29.2 (5.3)	<.001

(Continued)

Table 1. Continued

Variable	Category	Missing	No Injury, *n* (%)	Ureter Injury *n* (%)	*P*-Value
Sodium, mean (SD)		18001	138.9 (3.4)	139.0 (3.1)	.057
Blood urea nitrogen, mean (SD)		26484	16.2 (11.1)	14.7 (8.7)	<.001
White blood cell count, mean (SD)		13638	8.4 (4.6)	7.9 (4.0)	<.001
Hematocrit, mean (SD)		11879	37.9 (6.1)	37.6 (5.8)	.075
Platelet count, mean (SD)		13858	270.9 (103.2)	281.9 (108.5)	<.001
Creatinine, mean (SD)		16216	1.0 (.7)	.9 (.5)	<.001

Abbreviations: L, left; R, right; SIRS, systemic inflammatory response syndrome; ASA, American Society of Anesthesiologists; SSI, surgical site infection; PATOS, present at time of surgery; RVUs, relative value units.

implemented using scikit-learn and NN using TensorFlow/Keras.[12,13] All analyses were performed in Python (version 3.8). Code to reproduce this work is available at https://github.com/gomezlab/colorectal_predictors/tree/main/ureter_injury.

Results

The data set included 262,923 patients. Of these, 213,786 were used for training/validation, while 49,137 were used for testing. 12,229 patients who had prophylactic ureteral stents placed were excluded from analysis. 1519 (.578%) of patients experienced UI. The cohort consisted of 52% female patients, with an average age of 61.6. By procedure type, the rate of UI was 1.0% for left-sided colectomies, .7% for low anterior resection, and .2% for right-sided colectomies. By indication, the rate of UI was highest for chronic diverticular disease (.9%) and rectal cancer (1.3%) and lowest for colon cancer (.5%) and non-malignant polyp (.1%). The average work relative value unit (RVUs) for procedures with no UI was 26.8 compared with 29.2 for those with UI.

Of the 3 machine learning techniques, XGB performed the best, with an AUROC score of .774 (95% CI .742-.807), compared with .698 (95% CI .664-.733) for LR. Random forest and NN also performed well with AUROC scores of .738 (95% CI .704-.772) and .763 (95% CI .730-.796), respectively. Comparison using the DeLong test showed a significant difference between the AUROCs of XGB and LR with $P < .001$. Receiver operating characteristic curves are shown in Figure 1.

Gradient boosting also showed the highest performance in terms of AUPRC with a score of .031 (95% CI .027-.034), although RF showed very similar performance at .030 (95% CI .027-.034). The AUPRC score for LR was much lower at .013 (95% CI .011-.015), while NN scored .024 (95% CI .021-.027). Results for AUROC and AUPRC are summarized in Table 2. Precision-recall curves are shown in Figure 2.

We also calculated sensitivity, positive predictive value, and negative predictive value across a range of specificity thresholds. At 90% specificity, XGB showed a sensitivity of 38%, a positive predictive value of 2%, and a negative predictive value of 99.6%. At 50% specificity, XGB showed a sensitivity of 88%, a positive predictive value of 1%, and a negative predictive value of 99.9%. Results for sensitivity, specificity, positive predictive value, and negative predictive value for all thresholds are available in Table 3.

We also analyzed model performance for patients who had stents placed. Among patients who had ureteral stents placed, the rate of UI was .883%. For the XGB model, AUROC was .613 and AUPRC was .017. However, the average prediction for the XGB model was .007 for patients with stents compared with .003 those without stents, showing higher predicted average risk.

Using SHAP values, we identified which variables had the strongest influence as predictors in the XGB model. The type of procedure, complexity of procedure (assessed using work relative value units), indication for surgery, mechanical bowel prep, wound classification, emergency procedure, and operative approach had the strongest influence on model decision making (Figure 3).

Discussion

This study sought to create and validate machine learning-based models to predict UI during colorectal surgery and showed significant improvements in predictive ability compared with LR, as well as high accuracy in the test set. Analysis of model decision making showed that the type of procedure, procedure complexity, indication for surgery, and mechanical bowel prep were the most important variables. Model accuracy was much lower for patients who had ureteral stents placed, suggesting that ureteral stent placement changes the risk profile for UI, but the model agreed with surgeon assessment that these patients were at overall higher risk.

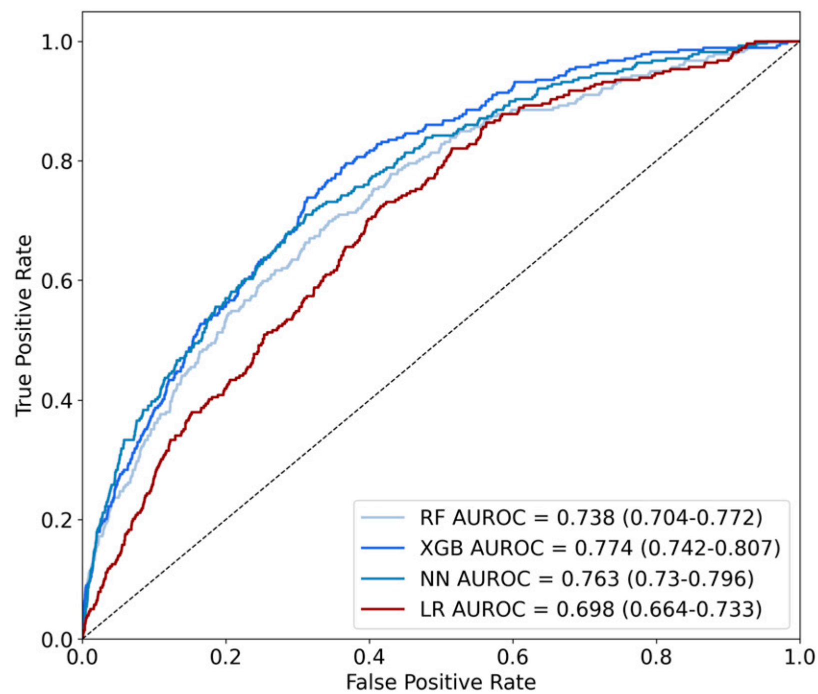

Figure 1. Receiver operating characteristic curves for models predicting ureteral injury. RF, random forest; XGB, gradient boosting; NN, neural network; LR; logistic regression; AUROC; area under the receiver operating characteristic curve.

Table 2. Area Under the Receiver Operating Characteristic Curve and Precision Recall Curve for Models Predicting Ureteral Injury.

Model	AUROC Mean	AUROC 95% CI	AUPRC Mean	AUPRC 95% CI
Logistic regression	.698	.664-.733	.013	.011-.015
Random forest	.738	.704-.772	.030	.027-.034
XGBoost	.774	.742-.807	.031	.027-.034
Neural network	.763	.730-.796	.024	.021-.027

Abbreviations: AUROC, area under the receiver operating characteristic curve; CI, confidence interval; AUPRC, area under the precision-recall curve.

Multiple previous studies have identified risk factors for UI during colorectal surgery.[14-16] The largest of these, an analysis using NSQIP from 2012 to 2014, found that UI was associated with diverticulitis, T4 malignancy, and open approach.[2] Additionally, a study using the Danish Colorectal Database from 2005 to 2011 found that laparoscopic approach and surgery for rectal cancer was associated with a higher risk of UI.[17] Our study contradicted this study's findings regarding operative approach, perhaps due to increased laparoscopic experience during the time period included in the NSQIP database. One previous study built a predictive model for UI during colorectal surgery using the National Inpatient Sample from 2001 to 2010 and showed an AUROC of .73.[1] However, this model required intraoperative information, including the presence of adhesions, limiting its use for preoperative decision making and inflating its accuracy.

One interesting finding from our study was the model's use of work RVUs as a risk factor for UI. While work RVUs are mainly used for financial compensation, they are also a measure of the complexity of operations. Work RVUs have been strongly associated with risk of postoperative complications in multiple previous studies.[18] In addition, other factors such as mechanical and oral antibiotic bowel prep are unlikely to have a direct influence on UI but are indirectly associated with decreased risk of injury, so have predictive value. Overall, there is a strong overlap between previously identified risk factors for UI and factors used by the current model. This confirms that one strength of machine learning approaches when applied to clinical risk prediction lies in improved

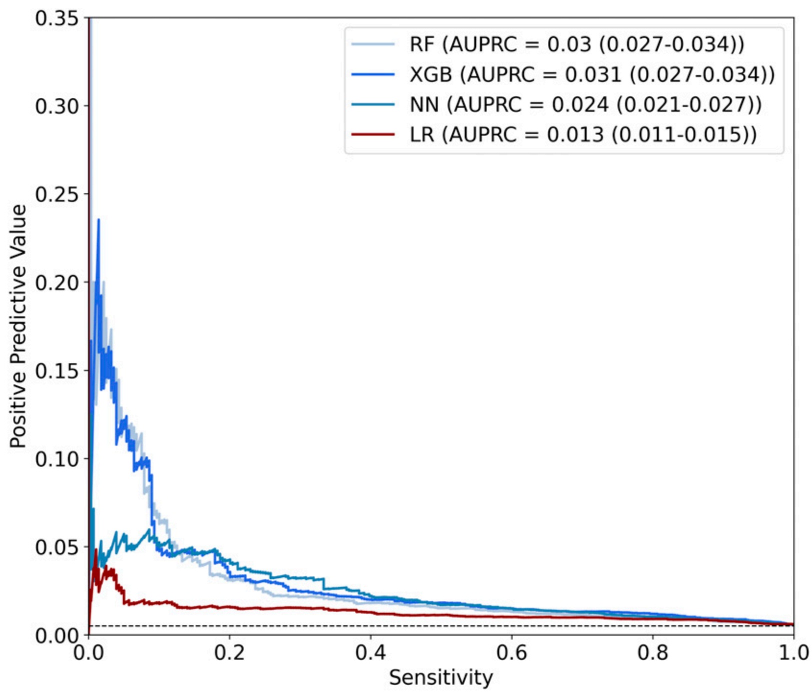

Figure 2. Precision-recall curves for models predicting ureteral injury. RF, random forest; XGB, gradient boosting; NN, neural network; LR, logistic regression; AUPRC, area under the precision-recall curve.

Table 3. Sensitivity, Specificity, Positive Predictive Value, and Negative Predictive Value for Gradient Boosting Models Predicting Ureteral Injury.

Specificity	Sensitivity	Positive predictive value	Negative predictive value
.90	.38	.02	.996
.70	.706	.013	.998
.50	.875	.01	.999
.30	.953	.008	.999
.10	.989	.006	.999

interpretation of known risk factors and their combinatory interactions rather than identification of novel ones.

Our model adds to the growing literature showing the potential for machine learning-based models to assist with preoperative decision making through risk prediction. Machine learning has shown high accuracy in predicting general postoperative outcomes across a variety of procedures and data sets.[5] More recently, it has been successfully applied to procedure and disease-specific outcomes including complexity of abdominal wall reconstruction and response of rectal cancer to neo-adjuvant therapy.[7,19] The current models similarly show the potential of using machine learning to incorporate information from large data sets and provide insights traditionally dependent on a surgeon's clinical judgment. If these models were integrated into the electronic medical record as decision-support tools, they could be used to automatically flag patients at the highest risk of UI for the consideration of stent placement. However, decision making would still be dependent on surgeons, who would choose the threshold at which they believe the benefits of stent placement outweigh the risks.

The study of iatrogenic UI is particularly difficult because it is so rare. This results in important limitations for the current study. The most significant is its method of identifying UI (with the use of CPT codes) within the NSQIP database. As noted by previous authors, this approach can incorrectly identify intentional concurrent resections of the ureter, although these cases are likely rare.[2,20] Additionally, it does not identify ureteral injuries which are not recognized intraoperatively and do not result in return to OR. Second, the models show low AUPRC and positive predictive value, which is expected given the rare incidence of UI and the importance of the operation itself in

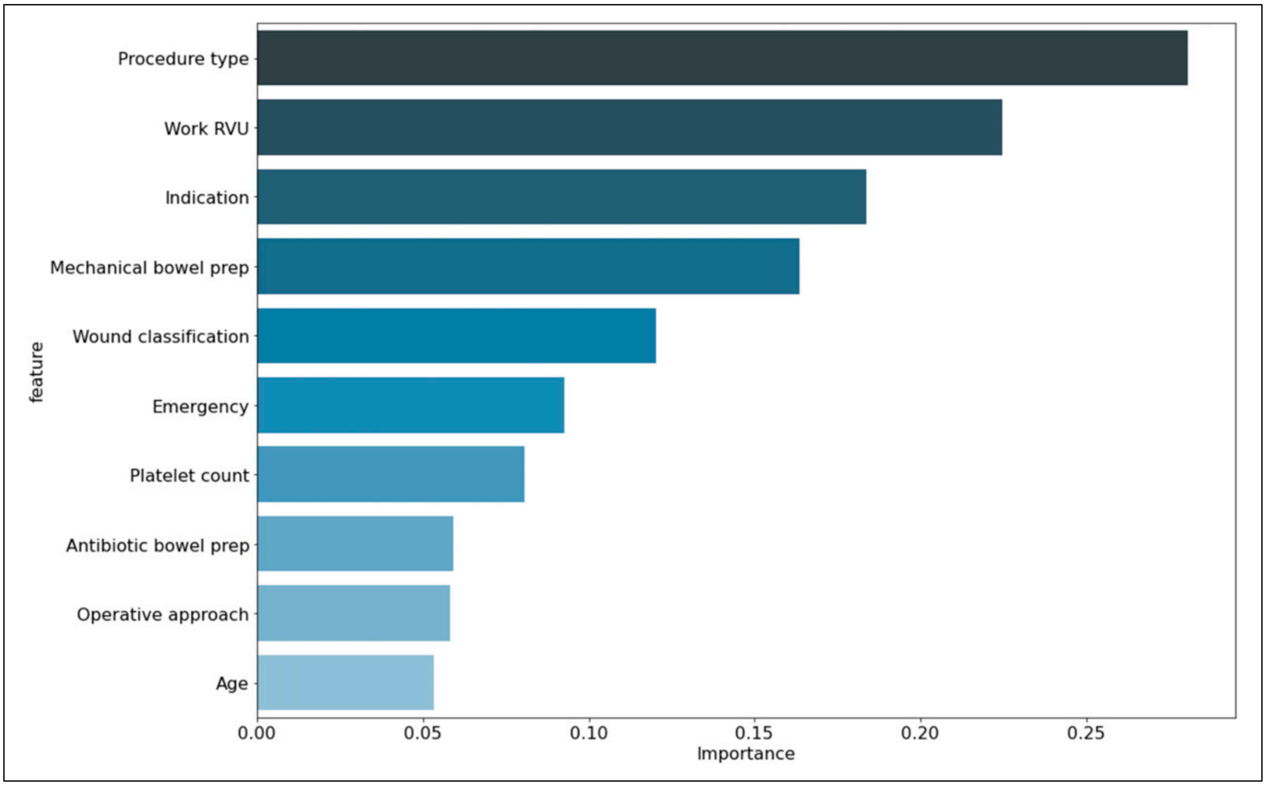

Figure 3. Importance of variables in predicting ureteral injury for the gradient boosting model. RVUs, relative value units.

causing injuries. Third, validation of the model on data external to NSQIP is difficult due to the low incidence of UI and models trained on the national NSQIP data set may not perform well at individual institutions. Fourth, our dataset does not include other preoperative information that may be helpful in predicting UI, such as a history of abdominal surgery or preoperative CT imaging. Finally, more accurate models specific to procedure type and indication are possible. However, we chose to balance model accuracy and generalizability by developing a model specific to colorectal surgery but useful for all colorectal resections.

Conclusion

In conclusion, this study shows that machine learning-based models can significantly outperform LR in the prediction of UI during colorectal surgery. Validation of these models will require assembly of a large, multi-institutional database in order to capture a sufficient number of events. However, with proper validation, these machine learning models could augment surgeon judgment by identifying patients at highest risk of UI for consideration of ureteral stent placement.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by funding from the National Institutes of Health (Program in Translational Medicine T32-CA244125 to UNC/KAC).

References

1. Halabi WJ, Jafari MD, Nguyen VQ, et al. Ureteral injuries in colorectal surgery: An analysis of trends, outcomes, and risk factors over a 10-year period in the United States. *Dis Colon Rectum*. 2014;57(2):179-186. doi:10.1097/DCR.0000000000000033
2. Coakley KM, Kasten KR, Sims SM, Prasad T, Heniford BT, Davis BR. Prophylactic ureteral catheters for colectomy: A national surgical quality improvement program-based analysis. *Dis Colon Rectum*. 2018;61(1):84-88. doi:10.1097/DCR.0000000000000976
3. Geavlete P, Georgescu D, Mulțescu R, Stanescu F, Cozma C, Geavlete B. Ureteral stent complications - experience on 50,000 procedures. *J Med Life*. 2021;14(6):769-775. doi:10.25122/JML-2021-0352
4. Dolejs SC, Nicolas M, Maun DC, Lane FR, Waters JA, Tsai BM. Localizing ureteral catheters for left-sided colectomy and proctectomy: Do the risks justify the benefits? *Am J Surg*. 2022;223(3):505-508. doi:10.1016/J.AMJSURG.2021.12.025

5. Henn J, Buness A, Schmid M, Kalff JC, Matthaei H. Machine learning to guide clinical decision-making in abdominal surgery-a systematic literature review. *Langenbeck's Arch Surg*. 2022;407:51-61. doi:10.1007/S00423-021-02348-W
6. Kambakamba P, Mannil M, Herrera PE, et al. The potential of machine learning to predict postoperative pancreatic fistula based on preoperative, non-contrast-enhanced CT: A proof-of-principle study. *Surgery (St Louis)*. 2020;167(2): 448-454. doi:10.1016/j.surg.2019.09.019
7. Elhage SA, Deerenberg EB, Ayuso SA, et al. Development and validation of image-based deep learning models to predict surgical complexity and complications in abdominal wall reconstruction. *JAMA Surg*. 2021;156(10):933-940. doi:10.1001/jamasurg.2021.3012
8. Shiloach M, Frencher SK, Steeger JE, et al. Toward robust information: Data quality and inter-rater reliability in the American College of Surgeons National Surgical Quality Improvement Program. *J Am Coll Surg*. 2010;210(1):6-16. doi:10.1016/J.JAMCOLLSURG.2009.09.031
9. Géron A. *Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. Sebastopol, CA: O'Reilly Media; 2019.
10. DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: A nonparametric approach. *Biometrics*. 1988;44(3):837-845. doi:10.2307/2531595
11. Lundberg SM, Allen PG, Lee S-I. A unified approach to interpreting model predictions. https://github.com/slundberg/shap, https://github.com/slundberg/shap. Accessed October 21, 2021.
12. Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: Machine learning in python. *J Mach Learn Res*. 2011;12: 2825-2830.
13. Chollet F. *Keras*. https://github.com/fchollet/keras, https://github.com/fchollet/keras. Published Online 2015.
14. Shahait AD, Mesquita-Neto JWB, Girten K, Weaver D, Gruber SA, Gamal M. Iatrogenic ureteral injury and prophylactic stent use in veterans undergoing colorectal surgery. *J Surg Res*. 2021;265:272-277. doi:10.1016/J.JSS.2021.03.054
15. Beraldo S, Neubeck K, Von Friderici E, Steinmüller L. The prophylactic use of a ureteral stent in laparoscopic colorectal surgery. *Scand J Surg*. 2013;102(2):87-89. doi:10.1177/1457496913482247
16. Merola J, Arnold B, Luks V, et al. Prophylactic ureteral stent placement vs no ureteral stent placement during open colectomy. *JAMA Surg*. 2018;153(1):87-90. doi:10.1001/JAMASURG.2017.3477
17. Andersen P, Andersen LM, Iversen LH. Iatrogenic ureteral injury in colorectal cancer surgery: A nationwide study comparing laparoscopic and open approaches. *Surg Endosc*. 2015;29(6):1406-1412. doi:10.1007/s00464-014-3814-1
18. Meguid RA, Bronsert MR, Juarez-Colunga E, Hammermeister KE, Henderson WG. Surgical risk preoperative assessment system (SURPAS): III. Accurate preoperative prediction of 8 adverse outcomes using 8 predictor variables. *Ann Surg*. 2016;264(1):23-31. doi:10.1097/SLA.0000000000001678
19. Delli Pizzi A, Chiarelli AM, Chiacchiaretta P, et al. MRI-based clinical-radiomics model predicts tumor response before treatment in locally advanced rectal cancer. *Sci Rep*. 2021;11(1):5379-5411. doi:10.1038/s41598-021-84816-3
20. Zafar SN, Ahaghotu CA, Libuit L, et al. Ureteral injury after laparoscopic versus open colectomy. *JSLS J Soc Laparoendosc Surg*. 2014;18(3):e2014.00158. doi:10.4293/JSLS.2014.00158