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| RESEARCH ARTICLE

Predictive Analytics for Intraoperative Complications: Enhancing Perioperative Safety with AI

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| ABSTRACT

Intraoperative problems significantly impact patient safety and surgical outcomes, with early detection of such problems being important to improve perioperative care. This article explores algorithms of machine learning to predict intraoperative complications using preoperative and intraoperative data from a large retrospective cohort of 121,898 adult surgical procedures at a single academic medical center between 2012 and 2016. To model the prediction of outcomes such as acute kidney injury (AKI), delirium, deep vein thrombosis (DVT), pulmonary embolism (PE), and pneumonia, five models were trained: logistic regression, support vector machine, random forest, gradient boosting tree (GBT), and deep neural network (DNN). Combination datasets performed better than preoperative or intraoperative data alone. The highest AUROC was 0.91 (GBT; pneumonia), 0.85 (aKI; GBT), 0.88 (DVT; GBT), 0.76 (PE; DNN), and 0.999 (delirium; GBT) (Table 2). Including missing data variables yielded significant performance gain in all categories. SHapley Additive exPlanations (SHAP) discovered significant, patient-specific risk factors in a clinically relevant manner, thus enhancing interpretability. These findings demonstrate the potential for AI-driven predictive analytics to provide physicians with interpretable, real-time decision support, reduce complication rates and enhance perioperative safety overall.

| KEYWORDS

Predictive Analytics, Intraoperative Complications, Perioperative Safety, AI, Surgical Outcomes

| ARTICLE INFORMATION

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1. Introduction

Intraoperative complications are serious hazards during surgery, leading to increased mortality, prolonged length of stay, higher costs, and increased strain on perioperative resources (Hossain et al., 2024). It can also lead to problems such as cardiac instability and organ failure (Hasan, Farabi, et al., 2025). While a number of these are related to underlying patient or surgical risk factors, many of these issues can be prevented with early identification and treatment. While identifying high-risk patients during the surgical procedure remains a very challenging task, it provides an enormous opportunity to enhance treatment results with real-time clinical decision support in the operating room (Bratzler et al., 2005; Hamel et al., 2005; Healey et al., 2002; Turrentine et al., 2006).

Recent advancements in machine learning (ML) and artificial intelligence (AI) have shown much promise in predicting adverse surgical outcomes (Hasan, Biswas, et al., 2025). Previous studies have used only intraoperative measures and preoperative patient variables to predict surgical complications and death; now models are increasingly being fed dynamic, real-time data. However, several limitations remain (Ferdousmou et al., 2025). First, the contribution of intraoperative data alone to risk prediction is unknown, because most contemporary models do not differentiate between the predictive contribution of intraoperative information and preoperative information (Debnath et al., 2024). Second, more variability and missingness in intraoperative data from actual practice are common; however, the implications of this disparity in model performance are often neglected (Das et al., 2023). Third, few of these studies have utilized model-agnostic interpretability approaches to distil complex machine learning outcomes into actionable insights that are clinically relevant and can assist anesthesiologists and surgeons in the operating room (Hofer et al., 2020; Wang et al., 2016; Warner et al., 2016).

The outcomes of interest in this study were pneumonia, pulmonary embolism (PE), deep vein thrombosis (DVT), delirium, and acute kidney injury (AKI) (Chowdhury et al., 2023). These five issues were selected, due largely to their plasticity potential for change post-operatively, specifically with vigilance and minimization via early diagnosis (Chowdhury et al., 2023). These problems were important and relevant to the management of postoperative care in critical care surgical units, according to a recent study involving a large cohort of stakeholders (Abraham et al., 2021; Janssen et al., 2019; Vlisides & Avidan, 2019).

Our study aims to (1) determine the predictive ability of specific machine learning models using preoperative, intraoperative, and combined data for postoperative complications (2) examine the relationship between prediction performance and the missingness of our input variables (3) provide model-agnostic, clinically relevant interpretations to assist both clinical decision making and care planning (Biswas et al., 2024).

2. Methodology

2.1 Sources of data

We trained machine learning models to predict clinically relevant intraoperative events based on both retrospective and real-time data obtained from adult patients who underwent surgery between 6/1/13 and 8/31/17 (Bhuiyan et al., 2025a). Data were extracted from the electronic anaesthesia record system (Meta Vision, iMDSoft) and the patient's electronic health record. The primary purpose was to identify intraoperative problems, with a view to improving perioperative safety (Bhuiyan et al., 2025a). The study was reviewed and approved by the institutional review board of the Washington University School of Medicine in St. Louis with the waiver of informed consent by virtue of the study's retrospective design (Arpita et al., 2025). Data from the study were not de-identified. The study was carried out in adherence to the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOOD) reporting guideline for the data sources, preprocessing techniques and modelling pipeline (Ali Linkon et al., 2024; Arpita et al., 2025).

2.2 Outcome Variable

The objective of this study was to investigate whether five conditions: acute kidney injury (AKI), delirium, deep vein thrombosis (DVT), pulmonary embolism (PE), and pneumonia were clinically significant around the time of surgery and thereafter (Al Mahmud, Hossan, et al., 2025). We selected specific complications for early identification and management. To identify AKI, we used serum creatinine concentration and dialysis event data; to evaluate delirium, we used CAM-ICU findings. ICD-10 diagnosis codes were used for PE, DVT and pneumonia, and patients without documented delirium evaluations were excluded (Al Mahmud, Dhar, et al., 2025).

2.3 Data and Data Processing

To prioritize preoperative and intraoperative variables to evaluate their predictive value for intraoperative morbidity was the goal of this study (Al Mahmud, Dhar, et al., 2025). Preoperative variables included age, sex, baseline physiological parameters, past medical history of diabetes and hypertension, type of anaesthesia and test results. During the surgical procedure, intraoperative data, including high-resolution time-series variables (vital signs, ventilator settings, and medication administration), were recorded at 1-minute intervals (Akter, Nilima, et al., 2024). Besides the list of variables and their availability in this data is a thorough description of data processing methods. Table 1 shows the variables and matching feature extraction techniques used for the model (Akter, Kamruzzaman, et al., 2024).

Table 1. The variables and matching feature extraction techniques used for the model.

Feature Category	Description	Data Processing
Categorical Patient Information	Gender, ethnicity, health score indices, physical and functional status, anesthesia and surgery types	Converted using one-hot encoding
Medical History (Categorical)	Includes cardiovascular, pulmonary, renal, metabolic, neurological, and oncological conditions, along with smoking history	Applied one-hot encoding for non-binary categories

Preoperative Vitals	Baseline measures such as blood pressure, heart rate, and oxygen saturation	Standardized using z-score normalization
Preoperative Lab Results	Blood test indicators like albumin, creatinine, glucose, and white blood cells	Standardized using z-score normalization
Intraoperative Vitals	Real-time vitals including multiple types of blood pressure, temperature, EEG data, and blood gases	Summarized using statistical features (min, max, mean, etc.) and normalized
Intraoperative Respiratory Parameters	Data from ventilators, like respiratory rate, tidal volume, and anesthetic concentrations	Statistical summarization and z-score normalization
Medications and Fluids During Surgery	Use of drugs such as norepinephrine, epinephrine, and vasopressin	Summarized using statistical features and normalized

2.4 Absent Information
Missing data were then imputed with a dummy indication technique for each of the preoperative variables such that indicator vectors indicated the absence of a preoperative variable and empty fields were filled with zeros. The final dataset was the imputed dataset for the data level or the features level (Ahmed et al., 2025). When some of the time series records in patient rows were missing data, data-level imputation was applied, where the patient mean was used to impute the data. Feature-level imputation was used in cases where the entire time series of a given patient's metric (e.g., the full set of temperature readings) was missing (Ahmed et al., 2025). Statistical characteristics of the metric were coded as missing and replaced with zeros in such cases (Ahmed et al., 2023). The absence of the time-series variables was then delayed through an indicator for whether the variable existed or was missing. Other imputation methods were explored, including fixed-value imputation methods (mean, median, and mode) and modern imputation methods (miss forest, k-nearest neighbor, and multiple imputation via chained equations) (Bhuiyan et al., 2025b).

2.5 Feature Development
The study employed a variety of feature engineering methods, including z-score normalization and one-hot encoding, to handle preoperative and intraoperative data (Chowdhury et al., 2023). Nine statistical characteristics were calculated, and z scores were normalized for intraoperative time series. A total of 712 features, comprising 81 unique dummy indicators, 505 features based on intraoperative factors, and 126 features based on preoperative variables, were retrieved from all clinical variables in the research (Das et al., 2023).

3. ML Models
Linear and nonlinear ML models were used to analyze three datasets: preoperative, intraoperative, and combined. In linear models, support vector machine and logistic regression were combined, while random forest, GBT, and DNN were used as nonlinear models (Goffer, 2025).

3.1 Model Performance and Evaluation
The performance of the model was assessed using five-fold cross-validation random shuffles. Where the results were fair, objective, the rare events were up-sampled according to the positive event-ratio of each complication (Goffer et al., 2025). The published study reported seven performance metrics: recall, accuracy, precision, and AUROC. Table 2 shows the cohort characteristics (Islam et al., 2025). The flow chart of cohort split and complication analysis is shown in Fig. 1.

Table 2. Cohort characteristics.

Category	Description	Value
Age	Mean (SD), y	54.4 (16.8)
Sex	Female	56914 (50.9%)
Race	White	82533 (73.8%)
Height	Median (IQR), cm	170 (163-178)
Weight	Median (IQR), kg	83 (69-100)
BMI	Median (IQR)	28 (24-34)
Functional capacity, METS	<4	17859 (16.0%)
Functional capacity, METS	4–6	24978 (22.3%)
Functional capacity, METS	>6	3094 (3.0%)
Functional capacity, METS	Missing	64632 (57.8%)
ASA physical status	Grade 1	6828 (6.1%)
ASA physical status	Grade 2	43758 (39.1%)
ASA physical status	Grade 3	48809 (43.6%)
ASA physical status	Grade 4	11858 (10.6%)
ASA physical status	Grade 5	609 (0.5%)
ASA emergency status	Emergency	8544 (7.6%)
Types of surgery	Cardiac	3677 (3.3%)
Types of surgery	Otolaryngology	3186 (2.8%)
Types of surgery	General	6624 (5.9%)
Types of surgery	Gynecology	4077 (3.6%)
Types of surgery	Neurosurgery	3776 (3.4%)
Types of surgery	Orthopedic	10416 (9.3%)
Types of surgery	Thoracic	2568 (2.3%)
Types of surgery	Urology	4889 (4.4%)
Types of surgery	Vascular	2669 (2.4%)
Types of surgery	Others	1825 (1.6%)
Types of surgery	Unknown	68181 (60.9%)
Comorbidity	Hypertension	23762 (21.2%)
Comorbidity	Pacemaker or AICD	2061 (1.8%)
Comorbidity	Prior stroke/TIA	1167 (1.0%)
Comorbidity	Peripheral artery disease	1920 (1.7%)
Comorbidity	Deep venous thrombosis	3597 (3.2%)
Comorbidity	Pulmonary embolism	1281 (1.1%)
Comorbidity	Diabetes mellitus	9331 (8.3%)
Comorbidity	Outpatient insulin use	7220 (6.5%)
Comorbidity	Chronic kidney disease	5949 (6.3%)
Comorbidity	Ongoing dialysis	3929 (4.5%)
Comorbidity	Pulmonary hypertension	2543 (3.3%)
Comorbidity	COPD	4312 (4.9%)
Comorbidity	Asthma	4883 (5.4%)

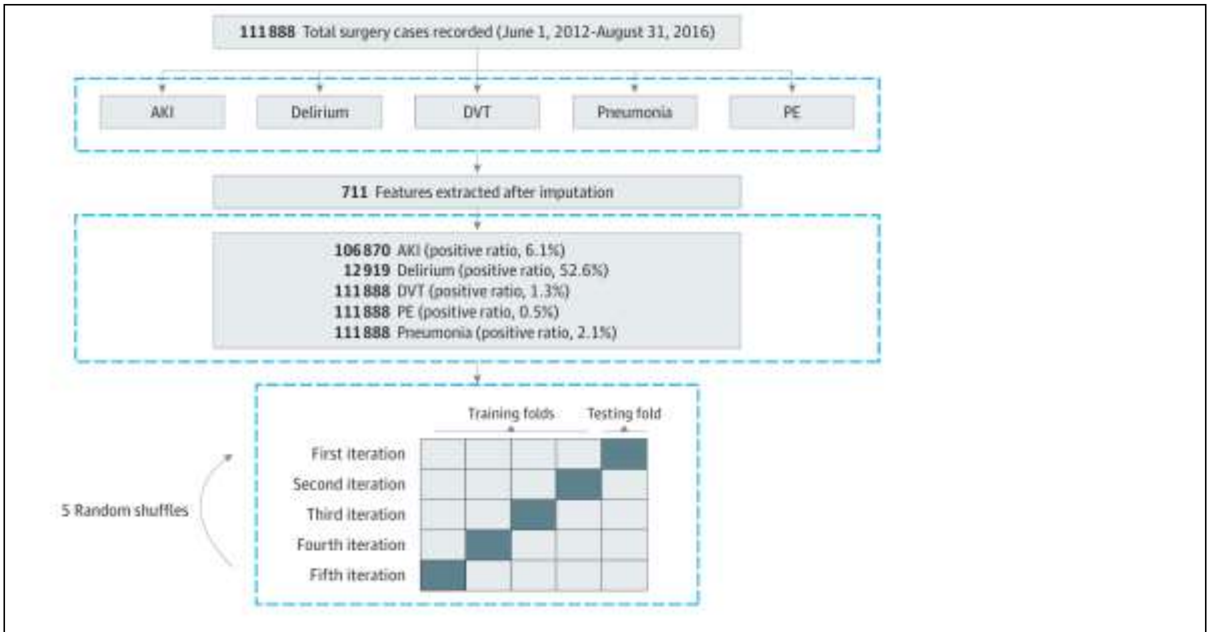


Fig. 1. Flow chart of Complication Analysis and Cohort Split (Kamal et al., 2025).

3.2 Model Interpretation
To interpret the model predictions, the study employs Shapley Additive exPlanations (SHAP). SHAP is a model-agnostic method for explaining model predictions (Mia Md Tofayel Gonee et al., 2020). The data were interpreted using SHAP (Shapley Additive exPlanations) value of individual trait that is, the number of units of deviation of that trait that increased the projected risk of a given complication. A positive SHAP score suggests a higher chance of complications, while a negative SHAP value indicates a reduced probability of complications. The size of the SHAP values indicated the contribution of the feature to prediction performance (Md Habibullah Faisal, 2022). In order to have clinical relevance, the SHAP values are transferred from the ML feature space back to the domain of interest (Khair et al., 2024). To focus on major attributes, the top ten characteristics were selected and retained based on their SHAP values (Mahmud, Orthi, et al., 2025). To contextualize intraoperative time series measurements by depicting their presenting statistical moments, the visualization aided in interpreting the model by showing cumulative risk accrued for each of the top ten clinical variables, and, for each of these variables, compared risk contributions for each of these variables against those for the average patient who was not a member of that complication cohort (Mahmud, Barikdar, et al., 2025).

3.3 Statistical Analysis
In this study, we performed two separate analyses. The first trial utilized preoperative datasets, data for intraoperative and combined datasets. The model was subsequently built and evaluated based on the features present in each dataset (Manik et al., 2025). In our second study, we explored the fact that we made improvements in prediction without increasing performance based on variables with varying levels of missingness (Khair et al., 2025). Each characteristic was ordered in ascending order of the rates of missingness (Md Ekrim et al., 2024). As described in the Analysing the Data section, we used those data available for all patients (complete case analysis, total missing rate 0%) before incorporating further variables (e.g. those with missingness). and generated it with both missing rates and feature sums predictable (Kaur et al., 2023).

4. Results
This cohort study included 111888 individuals with acute kidney injury (AKI), dialysis-induced pneumonia (DVT), and pneumonia. Pneumonia, AKI, DVT, and delirium were the top-performing GBT machine-learning models, whereas PE was best identified by DNN. The AUROCs for pneumonia, AKI, DVT, PE, and delirium were 0.905, 0.848, 0.881, and 0.762, respectively. The fake indication method worked great with the pneumonia dataset. The composite data set showed superior predictive performance than either the preoperative data set or the intraoperative data set. The best performance across all challenges was shown using a hybrid data set. But models that used only preoperative data performed nearly as well. With the introduction of more features, the AUROC increased progressively as the missing rates increased.

Some of the very relevant pneumonia features, such as pads for early mobilization, pulmonary hygiene with a respiratory therapist, scheduled bronchodilators and continuous epidural analgesia, accessory oxygen, continuous observation and low threshold for antibiotic treatment, presented in the ML output explanations are the kind of symptoms that will be leading for a timely clinical intervention in the intensive care settings. Compared to the community of individuals without disease, nine of the top 10 clinical characteristics with the most elevated SHAP values suggested a potential risk of pneumonia. Adding these top 10 clinical markers to the algorithm, the overall conditional probability of a pneumonia diagnosis may increase from 0.500 to 0.920. Fig. Two displays the results from the machine learning models. Fig. 3 shows the complication-specific model interpretation.

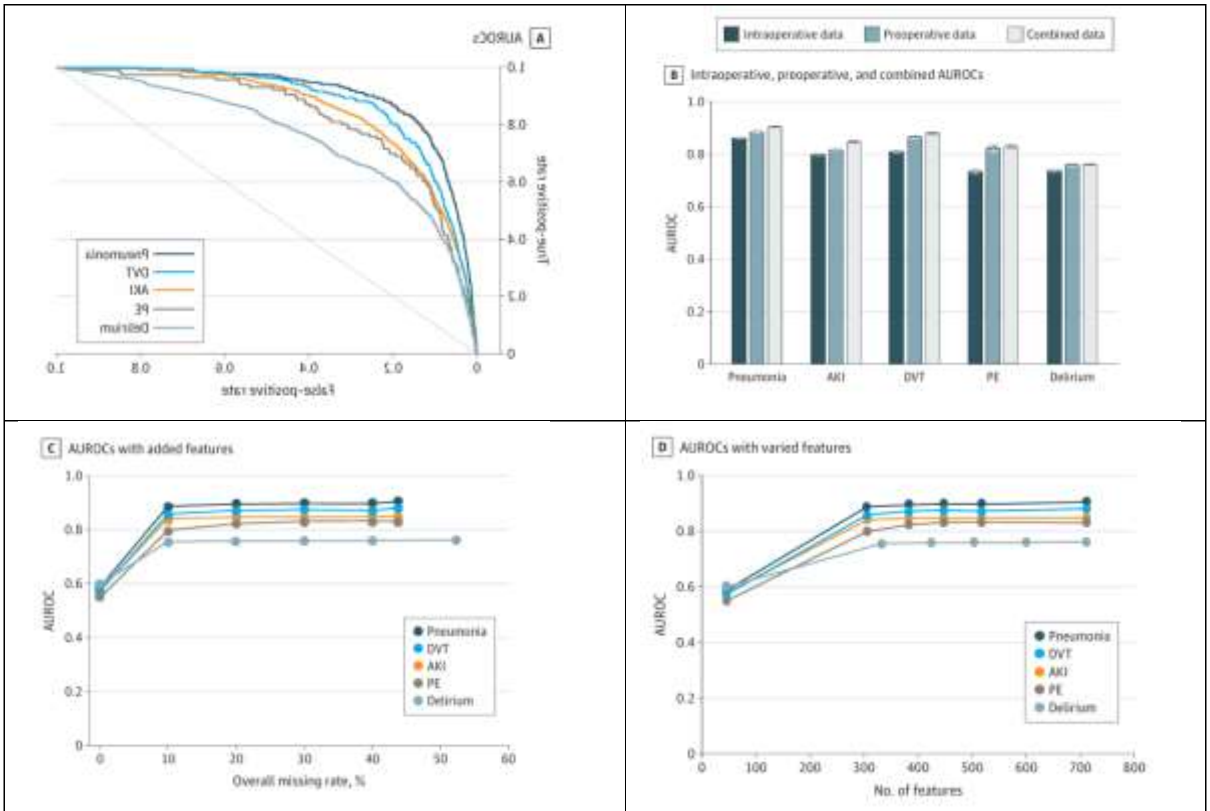
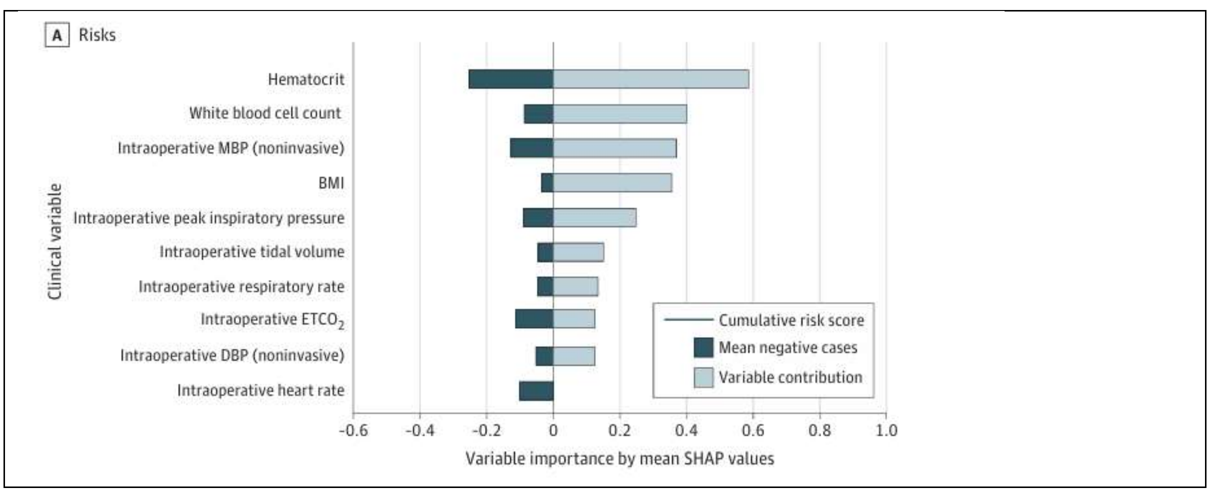


Fig. 2. Results of Machine Learning Models.



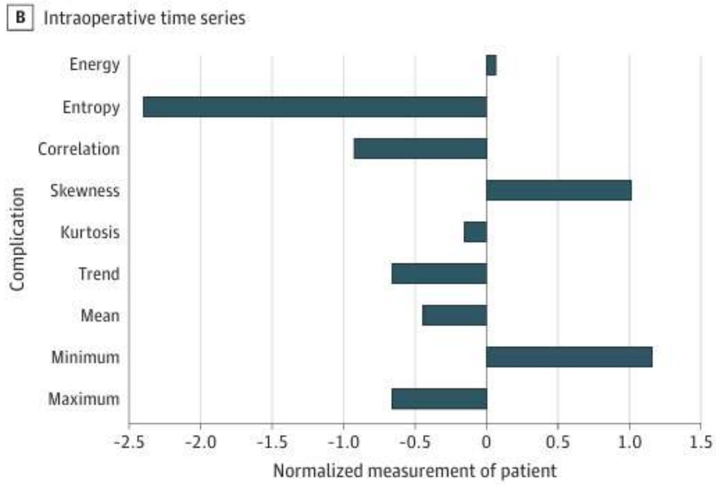


Fig. 3. Complication-Specific Model Interpretation

5. Discussion

This study utilized a machine learning approach using preoperative and intraoperative surgical data to predict postoperative surgical complications. GB and DNN were the best performing algorithms for PE, whereas gradient boosting tree and DNN performed best for pneumonia, AKI, DVT, and delirium. The data availability time over the perioperative continuum can further assist in predicting the potential clinical trajectory of the patient. Separate models were generated from preoperative, intraoperative, and combined data sets. These models may be used by practitioners to predict the preoperative and postoperative morbidities that help formulate care management, followed by the objectives and strategies. Also in the study, it was shown how the performance of predictions improved when variables were missing, and what effect that had on prediction performance. To generalize the interpretation tool to clinical communication, a model-agnostic interpretation method was also explored in this study for describing residues of clinical features that could lead to post-operative complications. This visualization style might help practitioners to evaluate evidence-based treatment procedures and ascertain important characteristics that influence the likelihood of complications. Another application of the prediction methodology could also be cognitive support, highlighting other clinical nuances, and validating/facilitating the estimation of the patients' risk for surgical complications for the attending.

6. Limitations

Limitations of this study include the use of surgical patient data from a single institution and not adjusting for the length of the procedure, planned surgical description, intraoperative variables, and commonly used drugs. There were too few patients to perform a subgroup analysis, and goal outcomes were identified with administrative data instead of human examination of the medical records. Current effort in an attempt to overcome these constraints is focused on performing data matches with manual quality health record checks.

7. Conclusions

These results indicate that machine learning can be deployed and implemented in the proposed machine learning framework for postoperative complications prediction with interpretability features. This framework could be implemented to deliver model-agnostic interpretation output within real-time clinical decision support systems and anticipatory management tools to guide practitioners in preparing postoperative directions and resource allocation.

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