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A Machine Learning Model for Predicting Postoperative Oxygen Requirement Among Surgical Patients in Rwanda Using Routinely Collected Patient Data

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Abstract

Background

Medical oxygen is crucial for safe postoperative care, yet data on its requirements post-surgery is scarce, particularly in resource-limited settings.

Objectives

The objective for this study were to identify the key predictors of postoperative oxygen requirement, develop and validate a machine learning model for predicting postoperative oxygen requirements among surgical patients.

Methods

A retrospective cross-sectional analytical study. Key predictors were identified using descriptive statistics, chi-square tests, and multivariable logistic regression. Nine machine learning algorithms were used to train and validate the model.

Results

Postoperative oxygen was required by 1,045 patients (28.0%). Key predictors included respiratory disease, higher ASA class, general anesthesia, prolonged surgery, anemia, blood loss, sleep apnea, pediatric or elderly status, and low baseline SpO_2. COPD/asthma was the strongest predictor. LightGBM achieved the highest accuracy (78.88%) and F1-score (77.94%), while XGBoost had the highest AUC (0.8163).

Conclusion

Machine learning showed potential for predicting postoperative oxygen requirements from routinely collected clinical data. LightGBM, XGBoost, and MLP demonstrated strengths across different performance measures. External validation is needed before clinical implementation.

Background of the Study

Globally, about 374 million people require medical oxygen each year, including 364 million people with acute medical and surgical conditions, of whom approximately 259 million are undergoing surgery regardless the increase during the covid 19 by 10%[1]. The hypoxemia also results into 17% of all deaths and those numbers demonstrate that oxygen is not a minor supportive intervention, but rather a

fundamental requirement for safe operative and postoperative management[2]. Postoperative hypoxemia, defined as reduced blood oxygen saturation less than 90% and partial pressure of oxygen less than 60-millimeter mercury after surgery, is recognized as one of the most frequent and clinically important respiratory complications in postoperative care[3]. During the postoperative period, many surgical patients require supplemental oxygen because of several physiological and clinical factors. These include the effects of anesthesia, surgical stress, postoperative pain, altered respiratory mechanics, residual neuromuscular blockade, opioid use, and hemodynamic instability, all of which may impair ventilation and oxygenation[4].

In general, surgical populations, postoperative pulmonary complications affect approximately 5% to 10% of patients and may include prolonged oxygen requirement, atelectasis, pneumonia, bronchitis, and respiratory failure[5]. A pooled analysis of 20 studies reported that the prevalence of postoperative hypoxemia was 20.6%. However, the prevalence varied considerably across different subgroups. It was higher in low- and middle-income countries, and further differences were observed according to the emergency status of the surgical procedure.[6].

Although oxygen is very important after surgery, it needs to be carefully monitored and titrated according to each patient's needs rather than given uniformly to all patients, because too little oxygen can lead to serious complications such as tissue hypoxia, arrhythmias, myocardial ischemia, poor wound healing, and other adverse outcomes, while too much oxygen can also be harmful, as both hypoxemia and hyperoxemia can be detrimental during the postoperative period[4]. This creates an important clinical challenge, particularly in busy and resource-limited surgical settings, where providers must determine which patients are most likely to require oxygen and when that need is likely to occur. In the study caried in Cleveland Clinic Main Campus and Juravinski Hospital in Canada, it was found that nurses while carrying out the post-operative monitoring, missed around 90% of the hypoxemia events and this would result in injuries when hypoxemia is prolonged[7].

Studies in African hospitals have revealed that surgical settings across Africa experience a pooled prevalence of postoperative hypoxemia of 33.81%, which is considerably higher than the global estimates of approximately 11% to 17%[6]. The burden appears to be even greater in sub-Saharan Africa, where study from Ethiopia have reported prevalence rates ranging from 36.6% to 47.9%[8]. These elevated rates are likely related to systemic challenges such as limited perioperative monitoring, inadequate oxygen delivery models, shortage of essential equipment, constrained critical care capacity, and insufficient numbers of trained personnel. Emergency and urgent surgical cases, which are common in low-resource settings, may carry an even greater risk of hypoxemia[9, 10]. Therefore, postoperative hypoxemia represents not only a frequent complication, but also a major patient safety concern in African surgical care.

A scoping review of 35 studies conducted across 22 sub-Saharan African countries showed that oxygen delivery models were available in only 42% to 94% of health facilities, often inconsistently, while pulse oximetry availability ranged from 0% to 64%; the same review also reported adult hypoxemia prevalence

of about 9% in Zambia and Malawi and 12.1% in another setting[11]. These findings, together with persistent shortages of equipment, unreliable electricity for oxygen concentrators, weak supply models, and limited staff training in many African health facilities, highlight major challenges in recognizing and managing oxygen needs effectively. Although this evidence confirms that oxygen requirement is an important issue in the region, most available studies focus on general hypoxemia and health system gaps rather than on postoperative oxygen requirement among surgical patients [12] .

A study conducted across Malawi, Kenya, and Rwanda showed that hypoxemia affected 7% of admitted adult patients, indicating that oxygen-related illness is an important problem in hospital care across the region[2]. The study also revealed weaknesses in oxygen monitoring and management, since only 18% of patients had complete oxygenation information recorded at admission, and 51% of hypoxemic patients experienced at least one day of receiving inadequate oxygen therapy. The outcomes were 35% of hypoxemic adults died during hospitalization, and 16% required mechanical ventilation, with almost half of these patients 49% not surviving[2]. These findings suggest that hypoxemia is not only common but also strongly associated with poor outcomes and severe clinical deterioration in sub-Saharan African hospitals

In Rwanda, oxygen is formally recognized as an essential component of safe anesthesia and postoperative care, and national policies continue to emphasize the need for stronger oxygen models, improved perioperative monitoring, and better health data infrastructure[13] .In the study conducted at CHUK on the use of oxygen on the Emergency department, it found that after educating the care providers the demand of oxygen increased from 18.% to 42% of intervention and this signifies how a tool that can facilitate the early identification of oxygen requirement would be important[14]. In addition, a multicenter study conducted at CHUK and CHUB showed that hypoxemia is common among hospitalized adults in Rwanda and that oxygen monitoring, documentation, and titration are often inconsistent, with evidence of both under-treatment and over-treatment [15]. Although this evidence was not specific to postoperative patients, it is directly relevant to surgical care because patients recovering from anesthesia also require timely oxygen assessment and appropriate titration.

Without adequate local evidence-based model, clinicians and hospital managers may have limited ability to identify high-risk patients early, prepare oxygen resources efficiently, and guide postoperative monitoring based on risk. Therefore, this study sought to develop a machine learning model for predicting postoperative oxygen requirement among surgical patients in Rwanda. By generating context-relevant evidence, the study is expected to contribute to improved postoperative care, better resource planning, strengthened patient safety, and broader national efforts to enhance anesthesia services, digital health use, and evidence-based surgical practice.

Methods

Study design

The study used a retrospective cross sectional analytical design based on routinely collected hospital records. This design enabled to examine perioperative data, identify predictors of oxygen requirement, and develop a machine learning model using real clinical data. The design was relevant to support the achieving the objectives of the study.

Participants' recruitment

The study population included all patients who underwent surgery at Kibagabaga Level Two Teaching Hospital in Kigali between 1 January 2024 and 31 December 2025 in surgical and maternity wards. The hospital was selected because it manages a high volume of surgical cases and provides a suitable setting for studying postoperative oxygen requirement. On average, the facility performs about 200 surgeries per month across gynecology, obstetrics, and surgical wards

Sampling strategy

This study used total enumeration sampling by including all eligible surgical records from Kibagabaga Level Two Teaching Hospital between 1 January 2024 and 31 December 2025. This approach was suitable because it used routinely collected hospital data and allowed the study to include as many relevant records as possible for model development. Although about 4,800 records were expected, data cleaning and eligibility screening resulted in a final sample of 3,738 patient records. This sample provided data for both predictor analysis and machine learning model development and internal validation.

Instrument

The study used a structured data extraction tool adopted from Machine learning prediction of oxygen therapy in pediatric Mycoplasma pneumoniae pneumonia study[16], Predicting the necessity of oxygen therapy in the early stage of COVID-19 using machine learning[17], The Epidemiology and Impact of Hypoxemia in Sub-Saharan Africa Prevalence, Practices, and Outcomes[18] and they were modified to meet the study being carried out.

Data collection

Data for this study were extracted primarily from OpenMRS at Kibagabaga Level Two Teaching Hospital. A 5000 rows dataset were extracted and transferred into Microsoft Excel, with paper-based records reviewed to check consistency against the electronic data. Extracted records were assessed for completeness, and a subset was validated against the original source documents to confirm accuracy. Data cleaning addressed missing values, duplicate entries, inconsistencies, and implausible observations, resulting in a final analytic sample of 3,738 eligible records.

Data analysis

Descriptive statistics were carried out using Stata, chi-square tests, and multivariable logistic regression were used to characterize the sample and identify factors associated with postoperative oxygen requirement.

Machine learning development

The model development followed the CRISP-DM framework, while the software prototype used an Agile SDLC approach with React, Django, and PostgreSQL. The study represents internal validation only and did not include external validation or clinical deployment. For machine learning, the data were divided using a stratified 70:30 train–test split, and nine algorithms were compared: Logistic Regression, Random Forest, XGBoost, LightGBM, KNN, SVM, MLP, Tab Transformer, and Naïve Bayes Model performance was evaluated on the test set using accuracy, sensitivity, specificity, precision, recall, F1-score, AUC, with sensitivity prioritized to reduce missed oxygen-requiring patients.

Model architecture

The machine learning clinical decision-support model operates through a React web interface that connects to a Django backend using REST APIs. The backend handles user authentication, data validation, prediction requests, model training, and communication with a PostgreSQL database for storing prediction records and model settings. The model provides risk assessments for postoperative oxygen requirements and includes clinical recommendations. Future integration with electronic medical records is planned using HL7 FHIR and JSON data exchange. Security measures such as authentication, access control, and data privacy are implemented throughout the system.

[Insert Fig. 1 **here]**

Figure 1. *The model architecture of the machine learning model to predict postoperative oxygen requirement*

The overall architecture of the proposed machine learning model, including the web interface, backend services, database, and prediction workflow, is illustrated in Fig. 1.

Ethical consideration

Ethical approval

was obtained from the University of Rwanda College of Medicine and Health Sciences Institutional Review Board (CMHS IRB), reference number CMHS/IRB/354/2026. Permission to access and use retrospective hospital records was subsequently obtained from Kibagabaga Level Two Teaching

Hospital before data extraction. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and applicable research ethics requirements[19]. As the study relied exclusively on routinely collected retrospective hospital records, no direct contact with patients was required. The extracted data were used solely for data analysis, model training, and model testing. All data were stored securely in password-protected files and accessed only by authorized personnel. Study findings were reported in aggregate form to protect patient confidentiality and ensure that individual participants could not be identified.

Results

Descriptive results of the study variables

Descriptive analysis was done to summarize the main characteristics of the final dataset. The dataset included 3,738 surgical patient records. Most patients were female, gynecology and obstetrics formed the largest group of surgical cases. The dataset also included different surgical specialties, urgency status, anesthesia techniques, and postoperative destinations. These variables helped to describe the study population and provided important information for predicting postoperative oxygen requirement.

Table 1. **Descriptive results of the study variables**

Table 1
Descriptive results of the study variables

Variable	Category / Summary	Frequency	Percentage
Total records	Surgical patient records	3,738	100.00%
Sex	Female	3,007	80.40%
Sex	Male	731	19.60%
Age group	Pediatric cases	250	6.70%
Age group	Adult cases	3,488	93.30%
Surgical specialty	Gynecology and Obstetrics	2,430	65.00%
Surgical specialty	General Surgery	627	16.80%
Surgical specialty	Orthopedics	374	10.00%
Surgical specialty	ENT	187	5.00%
Surgery status	Emergency	2,129	57.00%
Surgery status	Elective	1,609	43.00%
Type of surgery	Major surgery	3,255	87.10%
Anesthesia type	Spinal anesthesia	1,819	48.70%
Anesthesia type	General anesthesia	1,295	34.60%
Postoperative Disposition	PACU	2,349	62.80%
Outcome	Postoperative oxygen required	1,045	28.00%
Outcome	Postoperative oxygen not required	2,693	72.00%

[insert Table 1 **here]**

Key Predictors of Postoperative Oxygen Requirement

To identify the key predictors of postoperative oxygen requirement, bivariate analysis was first conducted to compare selected clinical and surgical factors with postoperative oxygen requirement. Variables that were clinically important and showed meaningful association were then considered for logistic regression analysis. The outcome variable was postoperative oxygen requirement, categorized as “Yes” or “No”.

Bivariate analysis showed that postoperative oxygen requirement was more common among patients with COPD or asthma, pre-existing respiratory disease, ASA class III and above, low baseline oxygen saturation, prolonged surgery duration, high estimated blood loss, anemia, general anesthesia,

emergency surgery, elderly age, pediatric status, and sleep apnea. These factors were therefore considered important because they were related to reduced respiratory reserve, increased surgical stress, anesthesia exposure, blood loss, and postoperative respiratory compromise.

Table 2. **Predictors of the postoperative oxygen requirement**

Table 2
Predictors of the postoperative oxygen requirement

Predictor / Risk factor	Patients with factor	Required oxygen	Oxygen required (%)	Crude OR	p-value
COPD or asthma	89	70	78.7%	10.10	< 0.001
Pre-existing respiratory disease	187	128	68.4%	6.23	< 0.001
ASA class III and above	1,202	617	51.3%	5.19	< 0.001
Baseline SpO_2 below 95%	533	285	53.5%	3.70	< 0.001
Surgery duration above 120 minutes	457	226	49.5%	2.94	< 0.001
General anesthesia	1,295	545	42.1%	2.82	< 0.001
Estimated blood loss above 500 ml	1,587	627	39.5%	2.71	< 0.001
Anemia	728	325	44.6%	2.56	< 0.001
Elderly patients aged 65 years and above	182	83	45.6%	2.26	< 0.001
Sleep apnea	74	34	45.9%	2.23	< 0.001
Emergency surgery	2,129	713	33.5%	1.94	< 0.001
Pediatric cases	250	95	38.0%	1.64	< 0.001
Obesity	447	116	26.0%	0.89	0.314

[insert Table 2 **here]**

Logistic Regression Analysis of the postoperative oxygen requirement

A multivariable logistic regression analysis was then conducted to identify independent predictors of postoperative oxygen requirement after adjusting for other factors. To reduce overlap between similar respiratory variables, COPD or asthma was included in the regression model as a specific respiratory condition. The model included clinical and surgical factors that were important in the bivariate analysis and were also clinically meaningful.

Table 3. **Logistic Regression Analysis of the postoperative oxygen requirement**

Table 3
Logistic Regression Analysis of the postoperative oxygen requirement

Predictor	**Adjusted OR**	**95% CI**	**p-value**
COPD or asthma	8.27	4.58–14.93	< 0.001
ASA class III and above	2.98	2.43–3.67	< 0.001
General anesthesia	2.96	2.49–3.53	< 0.001
Surgery duration above 120 minutes	2.06	1.63–2.61	< 0.001
Anemia	1.90	1.55–2.33	< 0.001
Pediatric case	1.86	1.37–2.53	< 0.001
Estimated blood loss above 500 ml	1.86	1.54–2.25	< 0.001
Sleep apnea	2.11	1.21–3.67	0.009
Elderly age 65 years and above	1.57	1.08–2.28	0.017
Baseline SpO_2 below 95%	1.50	1.17–1.91	0.001
Emergency surgery	1.07	0.89–1.29	0.477
Obesity	0.83	0.64–1.09	0.185

[insert Table 3 **here]**

Machine Learning Model Development Results

Nine machine learning models were trained and internally validated to predict postoperative oxygen requirement, using accuracy, sensitivity/recall, specificity, precision, F1-score, and AUC for performance assessment. LightGBM achieved the highest accuracy (78.88%), followed by XGBoost (78.70%), Random Forest (78.07%), and Logistic Regression (77.54%). MLP demonstrated the highest sensitivity (74%), followed by LightGBM (51%), Naïve Bayes (50%), Logistic Regression (47%), and XGBoost (46%), whereas SVM had the lowest sensitivity (5.41%). Specificity was highest for MLP (99.38%), followed by SVM (99.26%), Random Forest (94.31%), and XGBoost (91.58%). LightGBM achieved the highest F1-score (77.94%) and precision (77.81%), followed by XGBoost (F1 = 77.25%; precision = 77.46%), while Logistic Regression recorded an F1-score of 76.43%; Random Forest and MLP had precisions of 76.98%

and 76.59%, respectively. XGBoost achieved the highest AUC (0.8163), followed by Random Forest (0.8092), LightGBM (0.8028), and Logistic Regression (0.7992), indicating acceptable discrimination, while lower AUC values were observed for KNN, SVM, and TabTransformer, with TabTransformer recording 0.561. Overall, LightGBM and XGBoost demonstrated strong overall performance based on accuracy, F1-score, and AUC, whereas MLP demonstrated the highest sensitivity and therefore greater ability to identify patients requiring postoperative oxygen. These findings highlight a trade-off between overall predictive performance and sensitivity, which is particularly relevant when minimizing missed oxygen-requiring patients is a clinical priority.

[I**nsert** Fig. 2**]**

Figure 2.**The presentation of performance across different models in the developed model**

The comparative performance of the nine machine learning models across the evaluation metrics is presented in Fig. 2.

Confusion matrix of the model

The confusion matrix results indicated varying effectiveness among models in classifying postoperative oxygen requirements. Most models excelled at identifying patients not needing oxygen, evident from high true negative values. LightGBM led with 159 true positives for patients requiring oxygen, followed by Naïve Bayes (158), Logistic Regression (148), and XGBoost (143). In contrast, SVM and MLP displayed low true positives and high false negatives, risking delayed monitoring for patients needing oxygen. Thus, LightGBM, XGBoost, Logistic Regression, and Naïve Bayes are more clinically useful than SVM and MLP for identifying patients at risk for postoperative oxygen need.

Table 4. *Confusion matrix for the used models*

Table 4
Confusion matrix for the used models

Model	TN	TP	FN	FP
Logistic Regression	722	148	166	148
Random Forest	762	114	200	46
XGBoost	740	143	171	68
LightGBM	726	159	155	82
K-Nearest Neighbours (KNN)	717	84	230	91
Support Vector Machine (SVM)	802	17	297	6
Multi-Layer Perceptron (MLP)	644	187	127	164
Tab Transformer	557	128	186	251
Naïve Bayes	670	158	156	138

[insert Table 4 **here]**

Discussion

This study focused on assessing the key determinants that influenced postoperative oxygen requirement and the performance of the developed machine learning model, it also assessed how the machine learning models can support early identification of patients who may need oxygen after surgery using the data gathered routinely in perioperative period.

Discussion of Key Post-Operative Oxygen Requirement Predictors

The main outcome variable of this study was postoperative oxygen requirement. Among the 3,738 surgical patient records included in the final dataset, 1,045 patients required oxygen after surgery, representing 28.0% of the study population. This demonstrated the low prevalence in oxygen requirement compared to other services like NICU as the rate oxygen requirement is 76.0% according to the study carried 2025 [20]. The findings of this study showed that postoperative oxygen requirement was influenced by several clinical and perioperative determinants. The strongest predictors identified through logistic regression were COPD or asthma, ASA class III and above, general anesthesia, surgery duration above 120 minutes, anemia, pediatric status, estimated blood loss above 500 ml, sleep apnea, elderly age, and baseline SpO_2 below 95%. These findings suggest that postoperative oxygen requirement was not caused by one factor alone, but resulted from the combined effect of respiratory status, patient clinical condition, anesthesia exposure, surgical burden, blood loss, and age-related vulnerability.

Respiratory conditions were the strongest determinants in this study. Patients with COPD or asthma had significantly higher odds of requiring postoperative oxygen (AOR = 8.27; 95% CI: 4.58–14.93; p < 0.001). This result is consistent with international research demonstrating that patients with pre-existing respiratory conditions and COPD are more likely to experience postoperative hypoxemia and need oxygen support. A study conducted at Chengdu Hospital in China found that COPD increases the risk of oxygen requirement with an odd ratio of 2.783[21] .

ASA class III and above was also an important determinant of postoperative oxygen requirement (AOR = 2.98; 95% CI: 2.43–3.67; p < 0.001). This finding indicates that patients with more severe illness were more likely to need oxygen after surgery. This is consistent with the WHO_2SAFE study from Thailand, which identified ASA class III and above as one of the predictors of postoperative oxygen requirement at PACU discharge with odd ratio of 2[22]. The finding is also supported by African evidence, where patients with chronic disease and poor baseline clinical condition were more likely to develop postoperative hypoxemia with odd ratio of 5.5 or pulmonary complications[23] .

Baseline SpO_2 below 95% was another significant predictor of postoperative oxygen requirement (AOR = 1.50; 95% CI: 1.17–1.91; p = 0.001). This result aligns with evidence from worldwide, in Africa, especially in East Africa that indicates poor preoperative or pre-induction oxygen saturation is linked to postoperative hypoxemia. The study in India reported that low baseline or PACU oxygen saturation was linked with postoperative hypoxemia as in the study carried on 452 patients, 61 (13.5%) of them who developed SPO2 less than 94% required oxygen, while Ethiopian studies also identified low pre-induction or preoperative oxygen saturation as an important predictor as among all the patients who had SPO2 less than 94%, 45% required oxygen therapy[24].

Emergency surgery and obesity were not statistically significant after adjustment in the logistic regression model. Emergency surgery had an AOR of 1.07 (95% CI: 0.89–1.29; p = 0.477), while obesity had an AOR of 0.83 (95% CI: 0.64–1.09; p = 0.185). This differs from some global and African studies as emergency surgery and obesity were associated with postoperative hypoxemia or oxygen requirement where BMI of 25-29.9 and 30-39.9 were associated with postoperative hypoxemia with AOR of 2.588 and 2.411 respectively[25] .

In Rwanda, evidence specifically focusing on postoperative oxygen requirement remains limited. Previous Rwandan and regional studies have mainly described hypoxemia burden, oxygen monitoring gaps, and perioperative outcomes rather than identifying determinants of postoperative oxygen requirement using predictive modelling. Therefore, the findings of this study add local evidence by showing that respiratory disease, high ASA class, general anesthesia, prolonged surgery, anemia, blood loss, sleep apnea, age vulnerability, and low baseline SpO_2 were the main determinants of postoperative oxygen requirement among surgical patients at Kibagabaga Level Two Teaching Hospital

Model Performance

The machine learning models were evaluated using accuracy, sensitivity, specificity, precision, F1-score, AUC, and confusion matrix to assess their ability to distinguish patients who required postoperative oxygen from those who did not. No single model performed best across all metrics: LightGBM achieved the highest accuracy and F1-score, XGBoost the highest AUC, and MLP the highest sensitivity.

In terms of accuracy, LightGBM performed best with 78.88%, followed by XGBoost with 78.70%, Random Forest with 78.07%, and Logistic Regression with 77.54%. This showed that the boosting models performed slightly better than the other models in correctly classifying the overall cases. These accuracies are considered as accepted as the baseline should be above 70%[26].In Rwanda, some machine learning study carried on chronic kidney disease prediction using XGBoost reported higher accuracy of 95.76%, and maternal health adverse outcome prediction models with accuracy around 86% [27, 28]. However, direct comparison is limited as that research employed different datasets and projected different outcomes. Therefore, the accuracy attained in this investigation was appropriate for a challenging postoperative clinical prediction challenge.

Sensitivity, MLP achieved the highest sensitivity at 74%, meaning it detected more oxygen-requiring patients than the other models. This finding was comparable to the German post-intubation hypoxia prediction study, where a neural network model achieved sensitivity of 74%[29]. For the study carried out in Rwanda about the prediction of the surgical sepsis prediction (Kigali Surgical Sepsis score), it achieved the sensitivity of 73%[30]. However, models such as XGBoost and LightGBM had lower sensitivity than MLP, even though they performed better in AUC and F1-score. This indicates that the most appropriate model depends on the clinical priority, whether overall predictive performance or early identification of patients requiring postoperative oxygen.

Specificity was generally high across several models. MLP had the highest specificity at 99.38%, followed by SVM at 99.26%, Random Forest at 94.31%, and XGBoost at 91.58%. In this study, MLP and SVM had even higher specificity than those reported studies. However, specificity alone was not enough to select the best model. When compared to the study carried in netherland on one million patients, on the ability of the machine learning to differentiate the case from the non-case on the liver failure, the specificity was 59% and sensitivity of 95%[31] .Though SVM had very high specificity but very low sensitivity of 5.41%, meaning it failed to identify most patients who actually required oxygen.

Precision and F1-score were used to assess the balance between correct positive predictions and missed oxygen-requiring cases. LightGBM achieved the highest F1-score at 77.94%, followed by XGBoost at 77.25% and Logistic Regression at 76.43%. LightGBM also had the highest precision at 77.81%, followed by XGBoost at 77.46%. These results showed that LightGBM and XGBoost had the best balance between identifying oxygen-requiring patients and maintaining reliable prediction performance. The higher precision and F1-scores of LightGBM and XGBoost suggest that these models provided a more consistent balance between correctly identifying patients requiring oxygen and limiting incorrect positive predictions. Comparing to the study carried out in 2020 about the predictor of the oxygen

supplement among covid patient in Japan, the logistic regression achieved the highest precision of 0.893 with accuracy of 0.900 and recall of 0.605 where the SPO2 were the most important predictor[32] .

The AUC results showed that XGBoost had the best discrimination ability, with an AUC of 0.8163, followed by Random Forest at 0.8092, LightGBM at 0.8028, and Logistic Regression at 0.7992. These values indicated acceptable discrimination because the models were able to separate patients who required oxygen from those who did not. The XGBoost AUC of 0.8163 is closer to the Prescience study, where machine learning learning were used to early prevent the hypoxemia during surgery achieved AUC values of 0.83 for initial prediction and 0.81 for real-time prediction[33]. The similarity in AUC values suggests that the models demonstrated comparable and clinically meaningful ability to discriminate between patients with and without postoperative oxygen requirements.

Overall, XGBoost and LightGBM demonstrated strong overall predictive performance, with LightGBM achieving the highest accuracy and F1-score, while XGBoost achieved the highest AUC. MLP achieved the highest sensitivity, making it important for identifying patients who actually required postoperative oxygen. Given that oxygen requirement is a patient-safety concern, model selection should consider clinical judgment alongside performance metrics. Thus, XGBoost or LightGBM may be suitable for overall prediction, while MLP may be considered when minimizing missed oxygen-requiring patients is the priority.

Limitations

The study had methodological, time, financial, and data-access limitations. The retrospective use of routine hospital records resulted in missing, incomplete, and inconsistent data, which reduced the available sample size and may have affected predictor quality and model performance. The use of data from a single hospital and internal validation also limited the generalizability of the findings to other healthcare settings in Rwanda. These limitations were mitigated through systematic data cleaning, appropriate preprocessing, clear inclusion and exclusion criteria, and selection of clinically relevant variables with acceptable completeness. Time and financial constraints were addressed through careful planning and prioritization of essential study activities, while data-access challenges were minimized by obtaining approvals early and collaborating closely with hospital staff to facilitate timely retrieval of eligible records and consult the registers.

Recommendations

Hospitals should strengthen the completeness, accuracy, and standardization of perioperative data to support quality care and future machine learning applications. Clinicians should use the model as a supportive tool alongside clinical judgment and routine patient assessment, particularly for high-risk patients. Health informatics implementers should ensure secure, user-friendly, and interoperable integration of the model into clinical workflows. Before wider implementation, the model should undergo external validation in other hospitals and settings. Continuous training, monitoring, data protection, and evaluation should be maintained to ensure safe, reliable, and clinically useful application.

Conclusion

This study developed and internally validated machine learning model for predicting postoperative oxygen requirements among surgical patients at Kibagabaga Level Two Teaching Hospital using 3,738 patient records.

Postoperative oxygen requirement was associated with patient-related and perioperative factors, particularly respiratory disease, higher ASA class, general anesthesia, prolonged surgery, anemia, blood loss, sleep apnea, pediatric status, advanced age, and low baseline SpO_2.

Among the nine algorithms evaluated, LightGBM achieved the highest accuracy and F1-score, XGBoost the highest AUC, while MLP demonstrated the highest sensitivity, indicating differences in model performance across evaluation measures.

The findings demonstrate the potential of routinely collected hospital data and machine learning to support early identification of patients at risk of postoperative oxygen requirement and improve postoperative monitoring and oxygen planning.

However, external validation in other healthcare settings is required to establish the model's generalizability, reliability, and clinical usefulness before routine clinical implementation.

Abbreviations

AOR
Adjusted Odds Ratio
API
Application Programming Interface
ASA
American Society of Anesthesiologists
AUC
Area Under Curve
CHUB
Centre Hospitalier Universitaire de Butare
CHUK
Centre Hospitalier Universitaire de Kigali
CMHS
College of Medicine and Health Sciences
COPD
Chronic Obstructive Pulmonary Disease
CRISP-DM
Cross-Industry Standard Process for Data Mining
FHIR

Fast Healthcare Interoperability Resources
HL7
Health Level Seven
IRB
Institutional Review Board
JSON
JavaScript Object Notation
Light GBM
Light gradient boosting machine
MLP
Multi-Layer Perceptron
NICU
Neonatal Intensive Care Unit
PACU
Post-Anesthesia Care Unit
SDLC
Software Development Life Cycle
SPO2
Peripheral Oxygen Saturation
SQL
Structured Query Language
SVM
Support Vector Machine
WHO_2SAFE
Wheezing, **O**besity, **O**perative time, **S**leep apnea, **A**SA classification, **F**emale, **E**lderly

Declarations

Declarations

Ethical and consents

Before conducting the study, the ethical clearance was obtained from University of Rwanda by College of Medicine Institutional Review Board (CMHS IRB) with reference number CMHS/IRB/354/2026 and the permission to access the patient's data were provided by Kibagabaga Level two Teaching Hospital. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and applicable research ethics requirements and the ethics that regulate the medical research in Rwanda[19] .

Informed consent

s: No informed consents required since no patients contact applied. The approval to access data were obtained from Kibagabaga Level Two Teaching Hospital administration.

Conflicts of interest:

The authors have no competing interest.

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Author Contribution

Author ContributionsAuthor M.J: Conceived the study and developed the research proposal and protocol. Prepared the research report and presented the study to the review panels of the University of Rwanda and Kibagabaga Level Two Teaching Hospital. Coordinated follow-up on ethical clearance from both institutions and led the overall research process.Authors J.M.V .H,C.M,F.H.M.A,T.S: Provided clinical and surgical expertise throughout the study. Advised on the clinical aspects of the research, monitored its implementation within the hospital, and helped ensure that the study was conducted in accordance with ethical principles and without harm to human participants.Authors G.M,N.I,N.R.I,E.K,P.D,B.I.R: Contributed to data collection and analysis, interpretation of the findings, and contextualization of the results in collaboration with the corresponding author.Authors M.U,E.M: Provided academic and research supervision, ensuring that the study was conducted in accordance with the research guidelines and

requirements of the University of Rwanda.Corresponding Author J: Coordinated the research process and collaborated with the relevant authors on data analysis, interpretation, and contextualization of the findings.

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Data availability

The dataset used in this study is not publicly available. It contains sensitive patient medical and surgical information. Access to the dataset is restricted in accordance with institutional confidentiality and data protection requirements. The data cannot be shared without prior authorization from the relevant hospital administration and compliance with applicable ethical and regulatory requirements.

References

1. Haile KE, Amsalu AA, Kassie GA, Asgedom YS, Chema TZ, Gebrekidan AY, et al. Prevalence of Postoperative Hypoxemia and Its Predictors among Surgical Patients in Ethiopia: A Systematic Review and Meta-analysis. J Perianesthesia Nurs. 2025. 10.1016/j.jopan.2025.07.007.
2. Sulani I, Onofrey LA, Trevisi L, Beane A, Brotherton BJ, Condo J, et al. The Epidemiology and Impact of Hypoxemia in Sub-Saharan Africa Prevalence, Practices, and Outcomes. Ann Am Thorac Soc. 2025;22(6):905–14. 10.1513/AnnalsATS.202410. -1092OC PubMed PMID: 40014052.
3. Olivas-Flores EM, Gonzalez-Ortega PH, Aceves JAG, Jazmin PM, Olivas-Flores EM, Gonzalez-Ortega PH et al. Acute Postoperative Hypoxemia. Postoperative Care and Complications [Working Title]. 2026 May 5. 10.5772/INTECHOPEN.1015608
4. Suzuki S. Oxygen administration for postoperative surgical patients: a narrative review. J Intensive Care. 2020;8(1):4–9. 10.1186/s40560-020-00498-5.
5. Admass BA, Ego BY, Tawye HY, Ahmed SA. Post-operative pulmonary complications after thoracic and upper abdominal procedures at referral hospitals in Amhara region, Ethiopia: a multi-center study. Front Surg. 2023;10(May):1–9. 10.3389/fsurg.2023.1177647.
6. Bizuneh YB, Zeleke ME, Gebru AM, Teshome DF, Mekonnen FA, Angaw DA, et al. Global prevalence of postoperative hypoxemia among adult and pediatric surgical patients: a systematic review and meta-analysis. BMC Anesthesiol. 2025;25(1):284. 10.1186/s12871-025-03146-3 . PubMed PMID: 40461977.
7. Kuschner O'connor, Butz AM. Postoperative Hypoxemia Is Common and Persistent: A Prospective Blinded Observational Study. Physiol Behav. 2017;176(12):139–48. 10.1213/ANE.0000000000000836.Postoperative.

8. Sulani I, Onofrey LA, Trevisi L, Beane A, Brotherton BJ, Condo J, et al. The Epidemiology and Impact of Hypoxemia in Sub-Saharan Africa Prevalence, Practices, and Outcomes. Ann Am Thorac Soc. 2025;22(6):905–14. 10.1513/AnnalsATS.202410. -1092OC PubMed PMID: 40014052.
9. Sharma Y, Obidigbo B, Oguama U, Ogbodo K, Prasad S, Paul I, et al. Adoption, Impact, and Economic Considerations of Pulse Oximetry and Oxygen Systems in African Surgical Care: A Narrative Review. Cureus. 2025;17(12):1–14. 10.7759/cureus.100203.
10. Stafford RE, Morrison CA, Godfrey G, Mahalu W. Challenges to the provision of emergency services and critical care in resource-constrained settings. Glob Heart. 2014;9(3):319–23. 08.005 PubMed PMID: 25667183.
11. Patil R, Shrivastava R, Juvekar S, McKinstry B, Fairhurst K. Specialist to non-specialist teleconsultations in chronic respiratory disease management: A systematic review. J Glob Health. 2021;11:1–16. 10.7189/jogh.11.04019 . PubMed PMID: 34326988.
12. Stein F, Perry M, Banda G, Woolhouse M, Mutapi F. Oxygen provision to fight COVID-19 in sub-Saharan Africa Commentary. BMJ Glob Health. 2020;5:2786. 10.1136/bmjgh-2020-002786.
13. Smith V, Changoor A, McDonald C, Barash D, Olayo B, Adudans S, et al. A Comprehensive Approach to Medical Oxygen Ecosystem Building: An Implementation Case Study in Kenya, Rwanda, and Ethiopia. Glob Health Sci Pract. 2022;10(6):e2100781. 10.9745/GHSP-D-21-00781/. -/DCSUPPLEMENTAL PubMed PMID: 36951289.
14. Sutherland T, Moriau V, Niyonzima JM, Mueller A, Kabeja L, Twagirumugabe T, et al. The Just Right Amount of Oxygen. Improving Oxygen Use in a Rwandan Emergency Department. Ann Am Thorac Soc. 2019;16(9):1138–42. 10.1513. /ANNALSATS.201811-763QI PubMed PMID: 31145642.
15. Sulani I, Onofrey LA, Trevisi L, Beane A, Brotherton BJ, Condo J, et al. The Epidemiology and Impact of Hypoxemia in Sub-Saharan Africa Prevalence, Practices, and Outcomes. Ann Am Thorac Soc. 2025;22(6):905–14. 10.1513/AnnalsATS.202410. -1092OC PubMed PMID: 40014052.
16. Coppola C, Andrew JJ, Ruggieri M, La Spina M, La Bianca MR, Leonardi S. Machine learning prediction of oxygen therapy in pediatric Mycoplasma pneumoniae pneumonia. Front Digit Health. 2026;8:1755878. 10.3389/FDGTH.2026.1755878/TEXT.
17. Saadatmand S, Salimifard K, Mohammadi R, Marzban M, Naghibzadeh-Tahami A. Predicting the necessity of oxygen therapy in the early stage of COVID-19 using machine learning. Med Biol Eng Comput. 2022;60(4):957–68. 02519-X PubMed PMID: 35147843.
18. Sulani I, Onofrey LA, Trevisi L, Beane A, Brotherton BJ, Condo J, et al. The Epidemiology and Impact of Hypoxemia in Sub-Saharan Africa: Prevalence, Practices, and Outcomes. Ann Am Thorac Soc. 2025;22(6):905. 10.1513. /ANNALSATS.202410-1092OC PubMed PMID: 40014052.
19. Sawicka-Gutaj N, Gruszczyński D, Guzik P, Mostowska A, Walkowiak J. Publication ethics of human studies in the light of the Declaration of Helsinki – a mini-review. J Med Sci. 2022;91(2):e700–700. 10.20883/MEDICAL.E700.
20. Mushumbamwiza H, Webster HH, Kayitesi C, Miller J, Chizyuka N, Musabirema F, et al. Hypoxemia detection and oxygen therapy practices in neonatal and pediatric wards across seven district and

referral hospitals in Rwanda. Front Pediatr. 2025;13:1526779. 10.3389/FPED.2025.1526779/FULL.

21. He Y, Chen Y, Zhang H, Zhou Y, Fu Q. Factors associated with postoperative occurrence of hypoxemia in patients undergoing total knee replacement surgery and its predictive model creation and validation. Med (United States). 2025;104(42):e45100. 10. 1097/MD.0000000000045100 PubMed PMID: 41189146.
22. Sungworawongpana C, Chaichulee S, Chaochankit W, Vichitkunakorn P, Gosiyaphant N, Thongaek CS, et al. The WHO2SAFE Score: A Predictive Tool for Postoperative Oxygen Requirement After PACU Recovery. J Clin Med. 2025;14(8). 10. 3390/JCM14082603 PubMed PMID: 40283435.
23. Haile KE, Amsalu AA, Kassie GA, Asgedom YS, Chema TZ, Gebrekidan AY, et al. Prevalence of Postoperative Hypoxemia and Its Predictors among Surgical Patients in Ethiopia: A Systematic Review and Meta-analysis. J Perianesthesia Nurs. 2026;41(2):483–e4912. 10.1016/j.jopan.2025.07. .007 PubMed PMID: 41217336.
24. Arıcı Parlak E, Ilkaz N, Ayhan H, İyigün E. Determination of Factors Affecting Oxygen Saturation During Transfer From the Operating Room to the Post-Anesthesia Care Unit. Eur Res J. 2026;347–57. 10.18621/EURJ.1849232.
25. Taye MG, Molla A, Teshome D, Hunie M, Kibret S, Fentie Y, et al. Predictors of hypoxemia after general anesthesia in the early postoperative period in a hospital in Ethiopia: An observational study. Multidiscip Respir Med. 2021;16. 10.4081/MRM.2021.782.
26. Powers DMW. Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation [Internet]. 2020 Oct 10 [cited 2026 Sep 26]. Available from: http://arxiv.org/abs/2010.16061
27. Fiacre RR, Majyambere S, Noella Confiance B, Germain N, Aliane U, Patrick N et al. Using Machine learning to predict chronic kidney diseases among diabetic patients in Rwanda [Internet]. 2024 Oct 23. 10.1101/2024.10.23.24315998
28. Kubahoniyesu T, Kabano IH. Predicting adverse pregnancy outcome in Rwanda using machine learning techniques. PLoS ONE. 2024;19(12):e0312447. 10.1371/. JOURNAL.PONE.0312447 PubMed PMID: 39637200.
29. Sippl P, Ganslandt T, Prokosch HU, Muenster T, Toddenroth D. Stud Health Technol Inf. 2017;243:212–6. 10.3233/978-1-61499-808-2-212 . PubMed PMID: 28883203. Machine Learning Models of Post-Intubation Hypoxia During General Anesthesia.
30. Niyongombwa I, Sibomana I, Karenzi ID, Kiswezi A, Rickard J. Kigali Surgical Sepsis (KiSS) Score: A New Tool to Predict Outcomes in Surgical Patients with Sepsis in Low- and Middle-Income Settings. World J Surg. 2020;44(11):3651–7. 10.1007/S00268-020-05708-7 . PubMed PMID: 32700110.
31. Afzal Z, Schuemie MJ, Van Blijderveen JC, Sen F, Sturkenboom MC, Kors JA. Improving sensitivity of machine learning methods for automated case identification from free-text electronic medical records [Internet]. 2013. 10.1186/1472-6947-13-30
32. Igarashi Y, Nishimura K, Ogawa K, Miyake N, Mizobuchi T, Shigeta K, et al. Machine Learning Prediction for Supplemental Oxygen Requirement in Patients with COVID-19. J Nippon Med School.

2022;89(2):161–8. JNMS.JNMS.2022_89-210 PubMed PMID: 34526457.

33. Lundberg SM, Nair B, Vavilala MS, Horibe M, Eisses MJ, Adams T, et al. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. Nat Biomed Eng. 2018;2(10):749. 10.1038/S41551-018-0304-0 . PubMed PMID: 31001455.

Figures

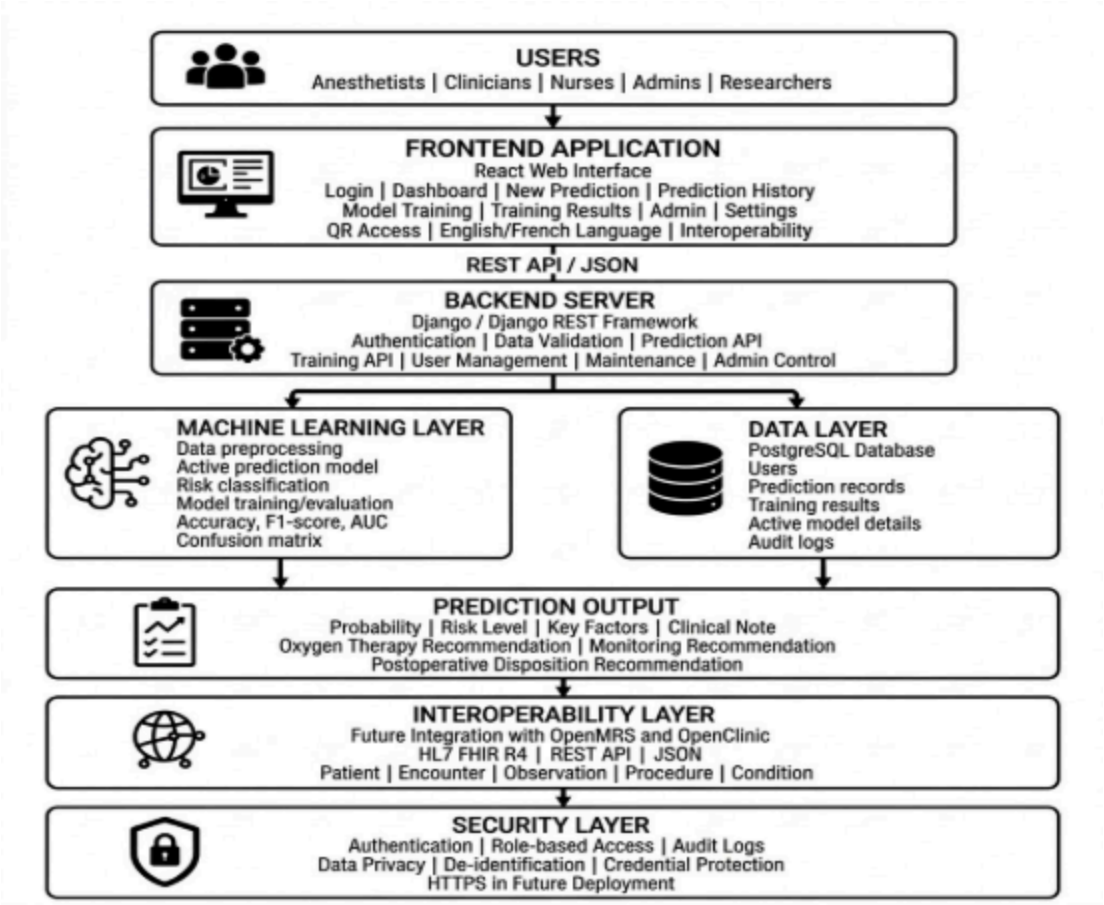


Figure 1

The model architecture of the machine learning model to predict postoperative oxygen requirement

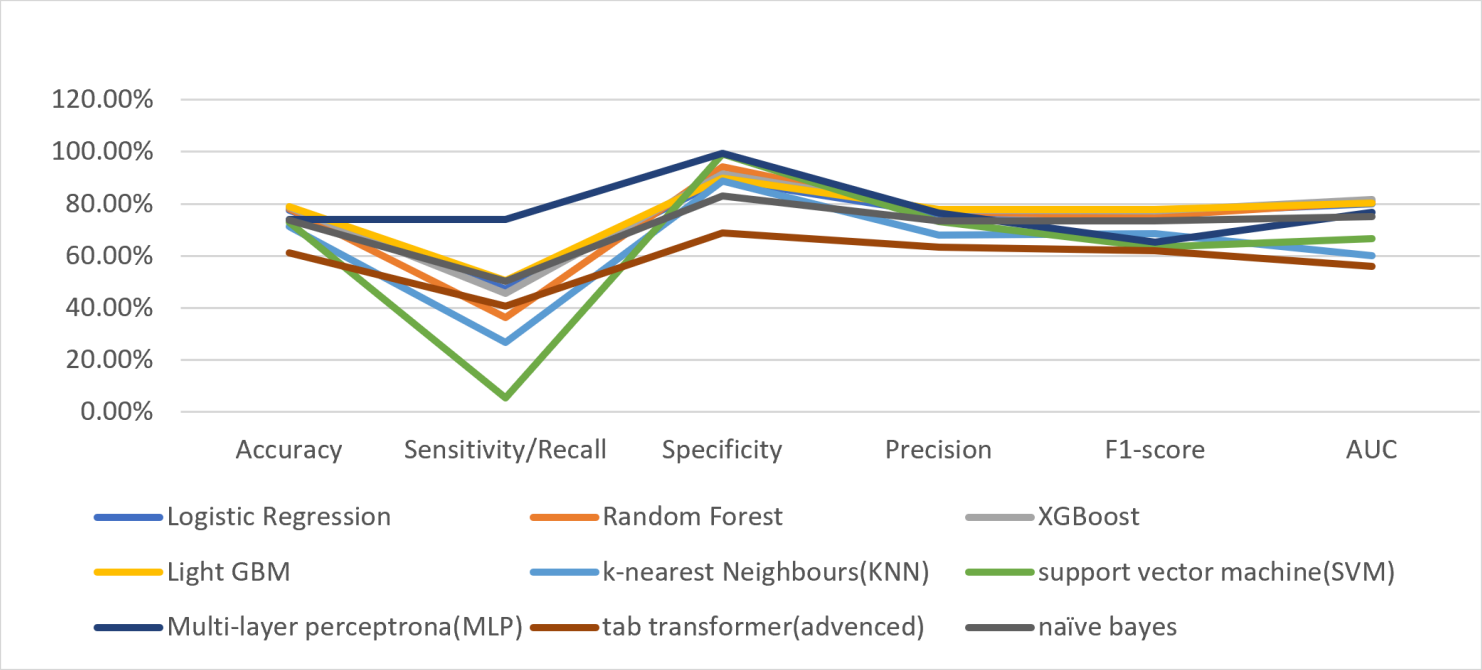


Figure 2

The presentation of performance across different models in the developed model