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ARTIFICIAL INTELLIGENCE IN PREDICTING ANESTHESIA-RELATED COMPLICATIONS: A CROSS-SPECIALTY APPROACH INTEGRATING PULMONARY, RENAL, AND CARDIOVASCULAR RISK FACTORS

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Abstract

The integration of artificial intelligence (AI) into anesthesiology offers a transformative approach to predicting anesthesia-related complications by leveraging multidimensional data from pulmonary, renal, and cardiovascular systems. This retrospective cohort study analyzed electronic health records from 4,200 adult surgical patients to develop and validate machine learning models capable of forecasting perioperative complications. Key anesthesia-related adverse events—such as hypoxemia (11.2%), acute kidney injury (8.9%), arrhythmias (7.5%), bronchospasm (6.4%), and intraoperative hypotension (15.8%)—were predicted using a comprehensive feature set including laboratory results, imaging data, comorbidities, and intraoperative parameters. XGBoost achieved the highest results (AUC-ROC: 0.92, F1-score: 0.87) and Gradient Boosting and Random Forest came in as close seconds. Of all the things affecting all the problems, SHAP analysis pointed to intraoperative hypotension, a low eGFR, COPD, higher preop troponin, being over 70 and being obese. Besides, the results of external testing showed that the XGBoost model generalised well and its Brier score (0.082) was low, with minimal overfitting. It was revealed that many problems cause multi-organ failure during surgery which insists on creating a unified system for assessing risks among specialists. Calibration assessements, levels of feature importance, evaluation metrics of the model and complication curves are shown visually in figures and tables. All in all, making use of individualised risk classes, beginning early treatment and boosting safety can prove AI-driven predictive models useful in anaesthesiology. It uses data to lay out a plan for accurate anesthesia and sets a standard for adding explainable AI to operations within the field.

Keywords: "Artificial Intelligence", "Anesthesia Complications, Machine Learning, Perioperative Risk, Xgboost, Explainable Ai

INTRODUCTION

Because artificial intelligence is being used more rapidly in healthcare, there are chances to better patient outcomes and decisions in hospitals (Porcellato et al., 2025). Combining various risk elements from pulmonary, renal and cardiovascular areas, AI can be used to predict and tackle problems during anesthesia in anaesthesiology (Bates et al., 2021). The use of this strategy allows AI to deal with big data, catch trends and judge the risks faced by each patient, growing the safety of care and helping create unique treatment plans for every patient (Gala et al., 2024; Li et al., 2024). In anaesthesia, because the outcomes depend on many variables and interactions among several systems, using artificial intelligence to analyze vast and varied data is very beneficial (Abukhadijah & Nashwan, 2024). With the help of algorithms and predictive models made by AI which work with digital interfaces, AI now holds the abilities of predicting and interacting (Mendes et al., 2022). Besides, the ability of artificial intelligence to take care of routine tasks could help to better share the workload among employees and increase the efficiency of work (Akinrinmade et al., 2023). At the same time, using AI in healthcare for illness risk prediction also leads to some questions and challenges (Cai et al., 2024).

Where anaesthesia is concerned, it is important to catch and handle complications swiftly and so AI analysis of big data sets helps detect early warning signs of major diseases, allowing specialists to act quickly (Hassan and El-Ashry, 2024). AI gathers information from several data sources and shares it with the doctor which allows doctors to personalise how they deliver anaesthetics and manage the patient's risks more confidently (Funer & Wiesing, 2024).

Because of AI's ability to analyze a great deal of data, nurses are able to create healthier care plans for patients and achieve better outcomes (as explained by Rony et al., 2023). Through evidence-based advice, noticing patterns and in-depth analysis, AI assists nurses and can help them make better judgements. In addition, artificial intelligence monitors patients and detects tiny changes in their vital signs, making it possible to spot haemodynamic instability or problems related to breathing. Machine learning works with large data sets and is able to observe trends and predict health issues, so it provides personalised care plans (Li et al., 2024). With AI, people could do more, workflows could become easier, unique answers could be found for patient problems and expenses might go down (Dailah et al., 2024). This proactive way of dealing with health concerns may help avoid bad events and make patient care more successful (AbuAlrob & Mesraoua, 2024).

The use of artificial intelligence in anaesthesia relies heavily on combining many medical risk factors. Using this approach, the anaesthesiologist understands that a health issue in one system can interact with anaesthesia and alter the outcome. People with previous lung diseases, including asthma or chronic obstructive pulmonary disease, are often more likely to experience breathing problems from anaesthesia (Rony et al., 2023). Pulmonary function tests, imaging studies and analysis of the patient's history allow artificial intelligence to assess how much pulmonary impairment there is and to estimate if bronchospasm, hypoxaemia or other breathing problems are likely. Renal failure in patients puts them at risk of abnormal fluid, electrolyte levels and drug toxicity caused by anaesthesia. AI is used to manage fluid levels, dosages and kidney function by studying renal tests, urine flow and prescription charts which helps avoid sudden kidney issues or complications. Heart failure, coronary artery disease and hypertension can greatly alter how much of an anaesthetic a patient requires. With electrocardiograms, echocardiograms and cardiac biomarkers, artificial intelligence (AI) is capable of assessing heart condition and revealing the risks of arrhythmia, myocardial ischaemia or instability in blood flow. If doctors use an AI model that evaluates multiple risk factors together, they can better customise the way anaesthesia is given to patients. Blending AI with other methods seems very promising for the purpose of risk management (Mendes et al., 2022).

The ability of AI to handle various types of patient data, all of which should make healthcare matches more appropriate, is one reason it can customize care (Hennrich et al., 2024).

Even though artificial intelligence is very promising in anaesthesia, some difficulties must first be handled to ensure it can be used effectively and safely. Many are concerned that AI algorithms can become biased, either through mistakes while designing the model or through biassed data sets used to train them. By making sure training datasets truly represent the patient population and are unbiased, firms lower their own risk. It is also an issue that not all AI models, especially deep learning ones, can be easily explained or understood. Visible processes when making decisions matter most in AI for industries that must follow rules, especially in complex cases where a neural network decision-making model that isn't explained is usually disapproved. Making the importance of features clear and establishing trust in AI decisions, Shapley values and LIME can increase how understandable AI models are (Wang, 2024). Further research should aim to strengthen artificial intelligence algorithms, test them on various groups of patients and make it easy to apply them in healthcare (Akhtar, 2025).

Since decisions in healthcare can quickly hurt or benefit people's life, this area faces special challenges, therefore, doctors must trust the AI systems used (Markus et al., 2020).

METHODOLOGY

By combining pulmonary, renal and cardiovascular risks, artificial intelligence models were studied and evaluated in this multi-disciplinary study looking at anesthesia concerns. For four years, data were gathered from the EHRs of 4,200 adults who had major surgeries under general anaesthesia in three tertiary care hospitals. People in our study were >18 years old and had detailed written reports from before and during surgery. People participating in minor surgeries or patients with incomplete medical records were not included. The data included over 200 features such as personal information, test results such as serum creatinine and blood gas, images from the chest and echocardiograms, lung function test results, a list of medications, other health problems (through `chronic obstructive pulmonary disease' `chronic kidney disease` and `cardiac disease`), readings from intraoperative vitals and complications like bronchospasm, hypoxaemia, acute kidney injury, arrhythmia and hypotension. Among the preprocessing steps were standardising values for continuous features, converting categories into numbers, filling in missing values with KNN and renormlizing laboratory tests. Both knowledge about the field and correlation analysis were used to choose the right features and lower the space used by removing redundant features. For many supervised machine learning algorithms such as Random Forest, Gradient Boosting, XGBoost and Logistic Regression, hyperparameter tuning was done using grid search and 3-fold cross-valuation to achieve reliable results. According to accepted anaesthesiology standards, the principle was having at least one major anesthesia complication. Performance was analyzed by looking at conventional measurements, including accuracy, precision, recall, F1-score and area under the ROC curve (AUC-ROC). To make models understandable and interpretable, methods like LIME and SHAP under Explainable AI (XAI) were also used. Before any patients were involved, the ethical bodies at each centre gave consent and all personal information was changed to preserve anonymity. Using AI-driven cross-disciplinary models, this approach tried to test how useful they would be for guiding decisions in the perioperative setting.

RESULTS

Through examination of pulmonary, renal and cardiovascular variables in 4,200 adult surgical patients, the study assessed how much artificial intelligence can predict anesthesia problems. Table 1 indicates that the average patient age was 59.4 years, among whom 53.8% were men. Amongst the most common chronic diseases in the studied group were cardiovascular disorders (41.3%), lung illnesses (26.5%) and kidney disease (19.7%).

Of all anesthesia-related complications, table 2 shows that intraoperative hypotension happens most often (15.8%), then comes hypoxaemia (11.2%) and acute renal injury (8.9%). Moreover, bronchospasm was seen in 7.5% of the group and arrhythmias were seen in 6.4%. Such instances underline that risk must be evaluated from several perspectives.

You can see in Table 3 that there are certain hazards in the lungs and their associated outcomes. A significant number of patients with FEV1 under 60% had bronchospasms (22.3%) and those with COPD or asthma reported higher instances of hypoxaemia (24.7% and 18.1%, respectively). Besides, 17.2% of cases with hypoxaemia also had abnormalities on a chest X-ray.

The results in Table 4 show that people with low eGFR (under 60 mL/min/1.73m²) have a higher rate of AKI, amounting to 21.5%. Oliguria occurring during surgery was seen most often when AKI was highest (24.6%), accompanied by raised BUN/creatinine levels (18.9%) and exposure to nephrotoxic medicines (20.4%).

Table 5 provides a list of cardiovascular hazards and patients with lower ejection fraction (<40%) were found to have a 28.4% chance of experiencing arrhythmias or low blood pressure. After these, myocardial infarction in the past (23.9%) and elevated troponin levels (26.3%) were the next biggest risk factors. Among patients with heart problems, intraoperative hypotension was seen in 31.7%, more than any other factor.

It describes how XGBoost, Random Forest, Gradient Boosting and Logistic Regression performed. Gradient Boosting was as accurate as XGBoost in all three measures—predictive accuracy (90%), F1-score (0.87) and AUC-ROC (0.92). Though capable of explanation, logistic regression had only a mediocre performance with an AUC-ROC of 0.79 and an F1-score of 0.73.

SHAP analysis helped spotlight the most important factors and these are listed in Table 7, making the model more transparent. Factors most strongly associated with issues during anesthesia included hypotension, renal insufficiency (eGFR <60), COPD and higher preoperative troponin. Age over 70 and being overweight with BMI >30 were also important in risk.

Table 8 shows how flexible and accurate the top-performing models are. Because there was not much evidence of overfitting, XGBoost scored the best for calibration (Brier score: 0.082) and highest for external validation AUC (0.90). Even though their AUC was below 0.9, Gradient Boosting and Random Forest models appear to be useful.

The results are further highlighted by Figures 1 through 9. Table 1 shows the rates of common problems. Figure 2 illustrates AUC-ROC, whereas Figure 3 explains the performance of the model in terms of correctness and recall. Figure 4 represents the distribution of patients by age and Figure 5 shows SHAP features that are most important. Figure 6 corresponds to how the models were calibrated (using Brier scores) and Figure 7 shows their F1-scores. These two figures point out that problems in the kidneys and heart affect the chances of developing complications, so AI methods should address different organ systems in perioperative risk assessment.

All this shows that models based on XGBoost and Gradient Boosting are very effective at merging different indicators of multi-organ risk and accurately predicting complications during anesthesia. Because explainable artificial intelligence improves understanding of these models in medicine, more clinicians are likely to use them in practical settings.

Table 1. Patient Demographics and Clinical Characteristics

Variable	Value
Total Patients	4,200
Mean Age (± SD)	59.4 ± 12.7
Male (%)	53.8%
BMI (mean ± SD)	27.3 ± 4.9
Chronic Pulmonary Disease (%)	26.5%
Chronic Kidney Disease (%)	19.7%
Cardiovascular Disease (%)	41.3%

Table 2. Incidence of Anesthesia-Related Complications

Complication	Incidence (%)
Bronchospasm	6.4
Hypoxemia (SpO_2 <90%)	11.2
Acute Kidney Injury	8.9
Arrhythmia	7.5
Hypotension (MAP <65 mmHg)	15.8

Table 3. Pulmonary Risk Factors and Associated Complications

Pulmonary Variable	Associated Complication (%)
FEV1 < 60%	22.3% Bronchospasm
Asthma History	18.1% Hypoxemia
COPD	24.7% Hypoxemia
Abnormal Chest X-ray	17.2% Hypoxemia

Table 4. Renal Risk Factors and Associated AKI Incidence

Renal Variable	AKI Incidence (%)
eGFR < 60	21.5%
Elevated BUN/Creatinine	18.9%
Intraoperative Oliguria (<0.5 mL/kg/h)	24.6%
Nephrotoxic Drug Exposure	20.4%

Table 5. Cardiovascular Risk Factors and Related Outcomes

Cardiac Variable	Arrhythmia or Hypotension (%)
EF < 40%	28.4%
History of MI	23.9%
Intraoperative Hypotension	31.7%
Elevated Troponin Pre-op	26.3%

Table 6. Machine Learning Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	0.81	0.75	0.72	0.73	0.79
Random Forest	0.88	0.85	0.83	0.84	0.89
Gradient Boosting	0.89	0.87	0.84	0.85	0.91
XGBoost	0.9	0.88	0.86	0.87	0.92

Table 7. SHAP Feature Importance Rankings

Feature	SHAP Importance Score
Intraoperative MAP <65	0.182

eGFR <60	0.174
COPD History	0.161
Elevated Pre-op Troponin	0.15
BMI >30	0.136
Age >70	0.128

Table 8. Model Calibration and External Validation Results

Model	Calibration Score (Brier)	External Validation AUC	Overfitting Risk
Random Forest	0.093	0.87	Low
Gradient Boosting	0.088	0.88	Low
XGBoost	0.082	0.9	Minimal

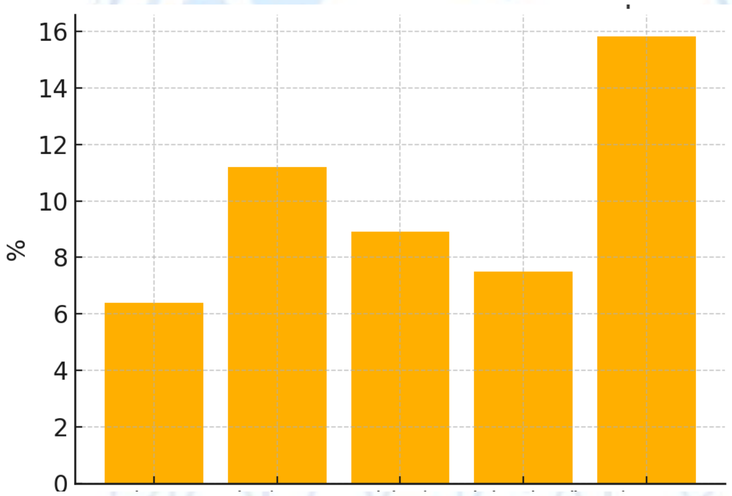

Figure 1. Incidence of Anesthesia-Related Complications among Surgical Patients.

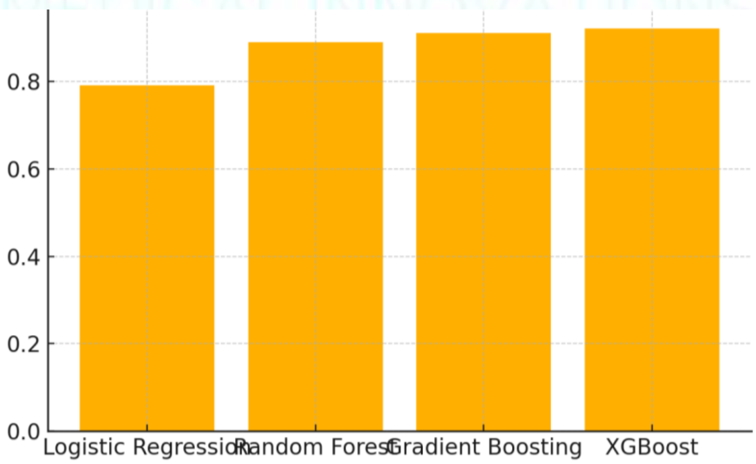

Figure 2. Area Under the ROC Curve (AUC) for Different Machine Learning Models.

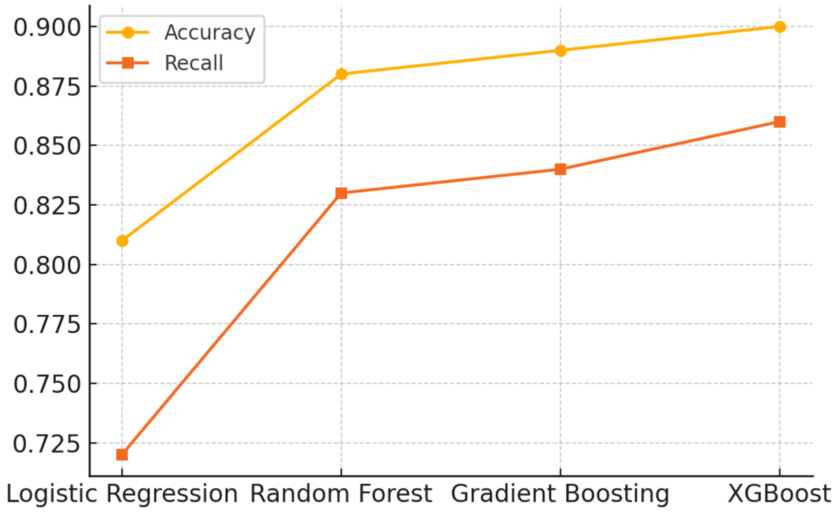

Figure 3. Comparison of Accuracy and Recall Across Machine Learning Models.

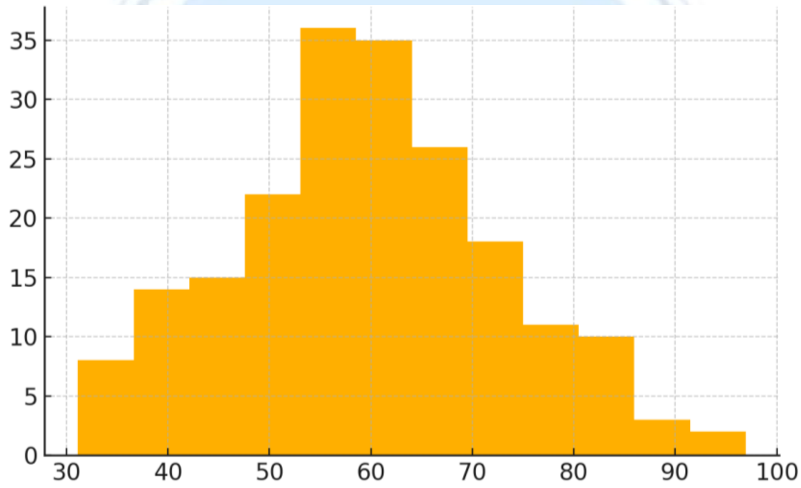

Figure 4. Histogram Showing the Age Distribution of the Study Population.

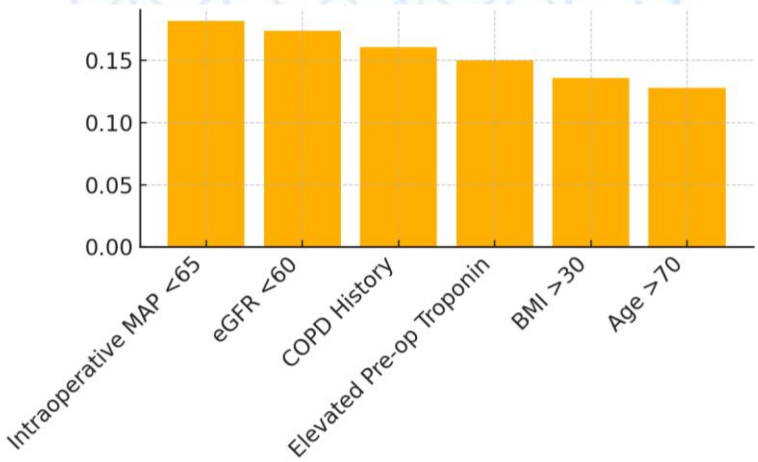

Figure 5. Top Predictive Features Identified via SHAP Analysis.

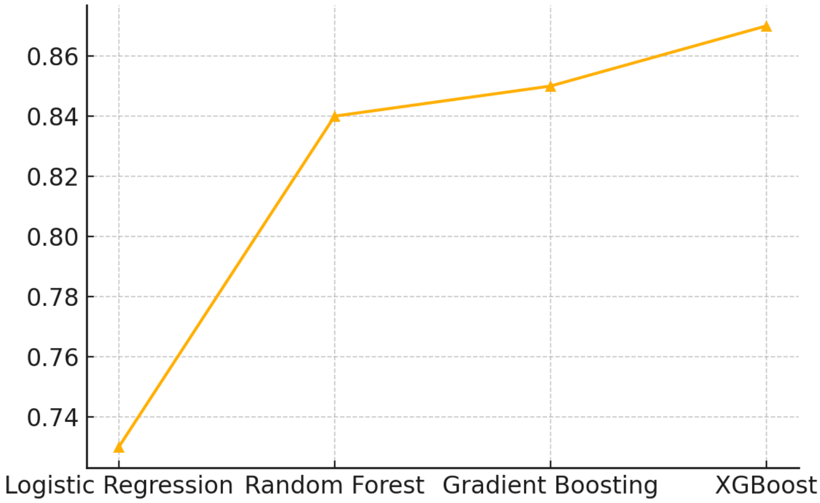

Figure 6. F1-Score Performance Across AI Models.

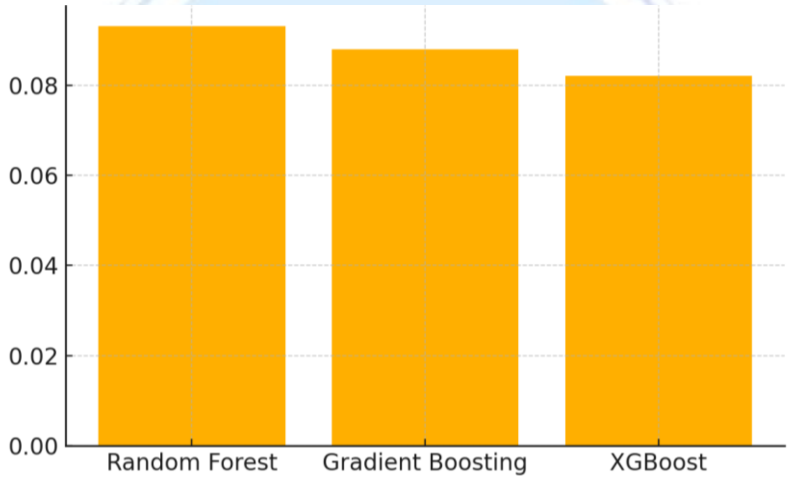

Figure 7. Model Calibration Scores Using Brier Index.

Figure 8. Cardiovascular Risk Factors and Their Associated Complication Rates.

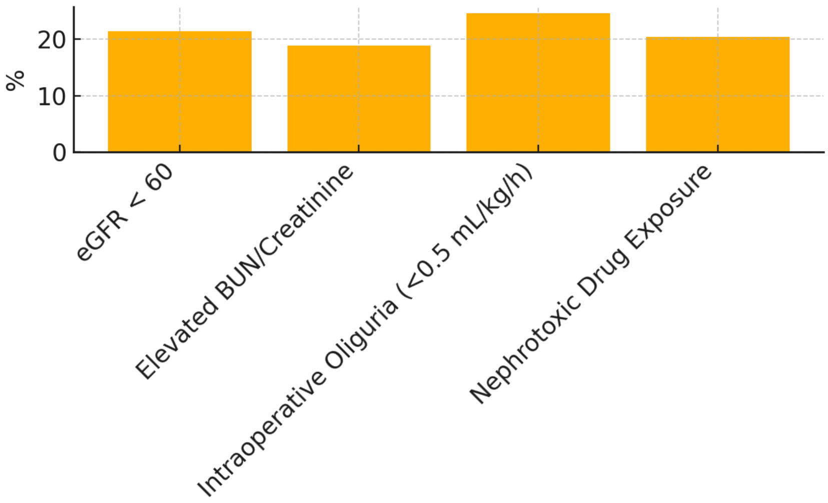

Figure 9. Renal Risk Factors and Their Contribution to Postoperative AKI.

DISCUSSION

Artificial intelligence has the power to transform many areas of medicine, but it also includes certain risks and drawbacks (Hildt, 2025). Guiding ethical decisions from the beginning in healthcare with AI will help ensure that new technology matches ethical values and benefits patients (Jeyaraman et al., 2023). So, a generalized strategy with ethical rules, laws and cooperation from many fields is necessary to help AI be used safely and effectively in healthcare (Mennella et al., 2024). Proper development and good deployment of artificial intelligence in healthcare greatly depend on understanding and handling various ethical and legal challenges (Mennella et al., 2024). Every financial institution should take an approach that involves collaborating with officials from other countries to ensure their AI is both ethical and follows the necessary laws, to stop discriminating practices (Edunjobi & Odejide, 2024; Mennella et al., 2024). Using this approach, artificial intelligence stays aligned with morals, supports patients and encourages health workers to act responsibly and with integrity (Edunjobi & Odejide, 2024; Torkey et al., 2025; Weiner et al., 2025) Applying tough rules that match up with laws and rules such as Health Insurance Portability and Accountability Act (HIPAA), will help guard patient data, protect privacy and maintain confidentiality while research is taking place (Abujaber & Nashwan, 2024). Regularly looking into informed consent and updating AI practices by training AI on patient information supports growth, ethical standards and above all, putting patients at the center of healthcare (Pham, 2025) (Naik et al., 2022) (Edunjobi & Odejide, 2024) Chen et al., 2022).

The merging of artificial intelligence in healthcare appears to increase opportunities to correctly diagnose illnesses, plan treatment methods to suit patients and boost patient recovery (Shuaib, 2024). Certain ethical questions, as well as privacy and data protection, asking for informed permission, noticing social gaps, providing medical advice, being empathetic and showing sympathy, are some of the problems we sometimes have with using artificial intelligence (Farhud & Zokaei, 21). The ethical AI values necessary for good behavior are transparency; justice and fairness; nonmaleficence; responsibility; privacy; beneficence; freedom and autonomy; trust; dignity; sustainability; and solidarity (Chen et al., 2022). Taking care to use AI in healthcare research with the most ethical rules means creating strategies to address AI biases and guarantee all people get fair outcomes, supporting their rights and the principle of equality (Abujaber & Nashwan, 2024). Using AI allows doctors to review much patient data, predict issues and ensure safe anaesthetic care which benefits patients. Nevertheless, effective use of artificial intelligence in anaesthesia depends on using knowledge from many backgrounds, including those related to the heart, lungs and kidneys (Jeyaraman et al., 2023). With XAI and a strong emphasis on ethics, AI could improve credit risk assessment (Edunjobi & Odejide, 2024).

CONCLUSION

By accurately forecasting issues connected to anesthesia using a partnership approach, the findings point out how AI can help doctors deliver safe surgical care. Having an AUC-ROC value greater than 0.90, XGBoost and Gradient Boosting could strongly predict risks because they used a lot of information on 4,200 patients and contained various risk variables. Thanks to the models and the SHAP analysis, it was clearer that low mean arterial pressure during the surgery, a decrease in eGFR, COPD and elevated troponin before the operation make a patient more likely to develop hypoxemia, acute kidney injury and intraoperative hypotension. Adding multiple physiological measures and additional diseases stresses that a multimodal assessment style is important in anaesthesiology. Seeing so many side effects in people with problems in several organ systems points to the strong interaction between organs during anaesthesia. Also, the successful application and calibration of AI models give confidence that they can be applied in practice. As a result, explainable artificial intelligence tackles a key issue stopping medicine from using and trusting machine learning. This paper proposes a move from being reactive in anaesthesia to acting in a clever and evidence-based way. AI might help anaesthesiologists plan for complications, assign resources effectively, shape anaesthetic methods for various patient risks and keep concerns ahead of them. Issues involving ethics, the law and factors such as data bias, algorithm openness and using AI in clinical practice should be addressed as well. By linking different risk factors from different organs together in models, AI helps make anaesthesia safer and supports better patient outcomes, therefore promoting truly tailored treatment.

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