Journal of Neonatal Surgery
ISSN (Online): 2226 -0439
Vol. 14, Issue 7 (2025)
https://www.jneonatalsurg.com

Machine Learning in Anesthesia: Overcoming Variability in Drug Response and Patient Sensitivity

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Cite this paper as: Dr Vinay Dandemmanavar, V. Rama Krishna, Sayyad Sadab Ali, Sriram K, Mr.Amandeep Singh, (2025) Machine Learning in Anesthesia: Overcoming Variability in Drug Response and Patient Sensitivity. *Journal of Neonatal Surgery*, 14 (7), 01-10.

ABSTRACT

Background: Patients exhibit different anesthesia responses because their genetic makeup and metabolic pathways and their medical conditions and their demographic background differ. Standard anesthesia dosing protocols fail to recognize patient differences so they deliver substandard drug effects and produce longer recovery periods and negative side effects. The advancement of machine learning (ML) and artificial intelligence (AI) enables data-driven predictive models to optimize customized anesthetic delivery thus producing better patient safety and operation results.

Objective: The research focuses on studying how individual patient characteristics affect anesthesia drug responses to create a predictive model that uses demographic and medical information for treatment outcome and adverse effect predictions.

Methods: The research analyzed 1,000 patient records containing information about demographics together with genetic predispositions and chronic conditions as well as drug allergies and symptoms and recommended medications and postoperative outcomes. The data preprocessing pipeline involved encoding categorical data and filling missing values and performing feature scaling along with detecting outliers. The application used supervised machine learning approaches to conduct both classification tasks for treatment effectiveness and regression tasks for recovery time prediction. The evaluation of the models included accuracy measures in addition to precision-recall metrics and RMSE (Root Mean Squared Error) to validate clinical applicability.

Results: The research study established meaningful statistical relationships between Body Mass Index values, patient age, ongoing health issues and how patients reacted to anesthesia. Higher Body Mass Index and preexisting medical conditions caused patients to show more variable drug metabolism patterns which resulted in 36.8% of adverse drug reactions. The XGBoost classifier delivered superior performance with 88.4% accuracy but Support Vector Regression (SVR) demonstrated the best recovery time prediction through 3.76 RMSE results. The research shows that predictive modeling based on ML operates effectively for optimizing anesthesia delivery.

Conclusion: The research demonstrates why AI-assisted anesthesia management requires attention to reduce drug response variability. Machine learning integration in perioperative care helps clinicians deliver precise dosing while reducing treatment side effects which leads to better patient safety outcomes. Research moving forward should concentrate on real-time AI-based systems for anesthetic monitoring to enhance dynamic and patient-specific dosage variations.

Keywords: *Machine Learning in Anesthesia*, *Personalized Anesthesia Administration*, *Artificial Intelligence in Perioperative Care*, *Adverse Reaction Prediction*, *Predictive Modeling in Anesthetic Response*

1. INTRODUCTION

Anesthesiology has experienced major breakthroughs regarding drugs and monitoring systems as well as procedural safety protocols. The substantial variations in how patients respond to anesthesia create a major medical challenge that produces inadequate drug performance and extended recovery durations together with unwanted side effects. The way anesthetic agents affect patients depends on multiple genetic and physiological and metabolic factors. The drug's metabolism together with its clearance rates and effectiveness face challenges because of these variations which demand precise dosage determination from a clinical perspective [1]. The medical field can solve this challenge through machine learning (ML) and artificial intelligence (AI) technology which predicts patient profiles and administers targeted anesthesia according to individual properties [2].

Surgeons and critical care practitioners rely on anesthesia to achieve controlled sedation together with patient analgesia along with stable medical procedures throughout surgical treatment. The current practice of determining anesthetic drugs and doses through empirical pharmacokinetic models bases its assumptions on population-wide standardization of drug responses. Clinical observations demonstrate wide variations between patients which produces excessive sedation and respiratory risks and inadequate anesthesia causing awareness during surgery [3]. The way patients react to anesthetics depends on their age combined with body mass index (BMI), genetic background and chronic health conditions and pre-existing drug sensitivities which necessitates individualized planning rather than being optional [4]. The field of pharmacogenomics alongside real-time monitoring systems has moved forward but medical decisions about anesthesia frequently depend on experimental tests instead of evidence-based predictive methods. Increasing interest in AI-driven methodologies has emerged because of the need for precise anesthesia care hence patient historical data together with machine learning algorithms and real-time biometric monitoring enables optimized anesthetic interventions [5]. Research publications present evidence that machine learning models achieve excellent accuracy when predicting how intraoperative hemodynamics evolve as well as postoperative discomfort levels and treatment length [6]. The developed models show promise for adverse reaction reduction and better perioperative results and superior patient safety outcomes. Standardized anesthesia protocols produce inconsistent patient results and cause delayed recuperation together with additional postoperative complications. The standardized dosing systems do not sufficiently understand how genetic elements combine with various medical issues alongside drug effects in the body. The administration of anesthesia requires individualized strategies due to unexpected drug reactions that occur when treating patients with unique metabolic profiles [7].

The research findings will improve precise anesthetic care by resolving three critical clinical problems:

1. Reducing unpredictability in anesthetic response through AI-based risk stratification.
2. Minimizing adverse drug reactions by leveraging predictive analytics for personalized dosing.
3. Improving patient safety and recovery outcomes by integrating ML-driven anesthetic management systems into clinical practice [8].

AI-assisted anesthesia brings about significant clinical effects in medical practice. Real-time predictive models installed for anesthesiologists help them choose optimal anesthetic substances and quantity decisions which reduces both surgical complications during procedures and delays following surgery. The research makes a contribution to the expanding AI application in perioperative medicine by establishing data-based methods for customized anesthesia treatment [9].

The research aims to achieve the following essential goals to overcome these obstacles:

1. To analyze the influence of patient-specific factors (age, BMI, chronic conditions, genetic disorders, and drug allergies) on anesthesia drug response, treatment effectiveness, and recovery time.
2. To develop and evaluate a machine learning model for predicting anesthesia drug response and adverse reactions based on patient demographics, medical history, and prescribed medication.

The research design uses machine learning techniques to quantify data from demographic, clinical and anesthetic outcome variables. The analysis uses classification models for treatment effectiveness predictions between Effective, Neutral and Ineffective categories while regression models calculate patient recovery times. This research evaluates the predictive models by measuring accuracy results and calculating root mean squared error (RMSE) and precision-recall performance levels. The research works to establish patient-specific models for anesthetic response which will boost perioperative care and enhance clinical decision-making abilities [10].

Artificial intelligence delivers its most significant value to perioperative medicine through personalized anesthesia. Wide research exists on pharmacokinetics and genetic determinants of anesthetic response but there are limited success stories of implementing AI-driven insights into actual medical practice. Anesthetic prediction modeling through machine learning systems provides the medical field with extraordinary opportunities to safeguard patients while choosing the right medicines and shortening their post-operative recovery period [1]. наявіа de anestesia baseada em inteligência artificial oferece potencial para melhorar a eficiência hospitalar e diminuir os custos relacionados a eventos adversos no setor de saúde e fornecer intervenções perioperatórias orientadas pela precisão. The findings from this study establish fundamental knowledge to merge data-based insights into everyday anesthetic decision processes [3].

The proposed study connects traditional anesthetic methods to contemporary predictive AI models through data-based strategies that help treat variable patient anesthetic responses. Research seeks to implement machine learning algorithms for anesthesia optimization with the goal to build new standards of individualized anesthesia care that enhances safety and operative effectiveness.

2. LITERATURE REVIEW

Medical anesthesiology has undergone major changes through the introduction of machine learning together with artificial intelligence which now provides precise strategies for administering drugs and evaluating patient risks and monitoring their condition. Current research on personalized anesthesia applies extensive study to genetic profiles together with AI-based decision systems along with real-time predictive models which enhance both safety and effectiveness of treatment. The adoption of AI-based anesthetic management systems has increased but healthcare professionals still need to achieve better patient response optimization and reduce drug side effects while designing workflows that support AI integration into clinical practice. The review explores contemporary developments while evaluating AI-driven anesthesia methods and their constraints together with their vacant areas to establish this work in current research fields.

Advanced medical practice in anesthesiology depends heavily on the use of AI alongside big data analysis for generating optimal drug choices and patient-tailored dosage methods. The application of AI algorithms for anesthesia complication prediction has significantly improved through recent research showing their capabilities for anticipating three essential operative results including hemodynamic changes and post-anesthesia pain and level of sedation [11]. Deep reinforcement learning enables real-time delivery of individualized anesthetic doses that reduces sedation-related problems and unstable blood pressure [12]. AI-powered components are now utilized with anesthesia information management systems (AIMS) to process extensive intraoperative information that provides real-time support for anesthesiologist decision-making [13]. The development of precision medicine in anesthetic care has advanced through genetic research that discovered important drug metabolism affecting polymorphisms. Research findings about genotype-based anesthetic protocols enabled doctors to develop protocols which help predict how drugs affect patients [14]. The implementation of AI-driven predictions faces ongoing difficulties when connecting them to real-time clinical decision-making because most AI models need extensive high-quality datasets to be reliable according to [15].

A variety of AI-based methods for anesthesia enhancement have been studied through federal learning algorithms combined with deep neural networks and reinforcement learning systems. Two supervised learning models namely random forest classifiers and support vector machines (SVMs) demonstrate high accuracy when used for patient recovery time prediction alongside anesthetic effectiveness assessment [16]. Medical data clusters utilizing unguided cluster techniques help classify patients according to their metabolic profiles which supports personalized anesthesia dosing decisions [17]. Numerous critical evaluations note AI models provide strong predictive capabilities but their practical usefulness remains limited due to diverse patient responses together with different surgical situations along with institutional variation in anesthetic practices [18]. Research compares traditional pharmacokinetic methods against AI-based dosing approaches which demonstrates superior performance from AI systems but requires continuous maintenance of real-time data input and training to preserve practical medical value [19]. The current research identifies interpretability as a major drawback of AI-based anesthesia models. Deep learning frameworks achieve excellent predictive performance yet their black-box operation receives criticism because validation and evidence-based guideline integration become complex tasks [20]. Researcher teams propose the creation of explainable AI (XAI) models to improve both model transparency and clinician trust during AI-assisted medical decisions [21].

The fast progress of AI in anesthesia encounters multiple essential deficiencies. The main challenge in AI development stems from the shortage of patient-specific datasets with high quality that can be effectively used for training purposes. The current research base uses retrospective data but such data fails to represent the full spectrum of actual anesthetic administration practices [22]. This research bridges the existing data gap through a structured information system containing patient demographic information combined with medical records and drug allergy notices and genetic profiles as well as response evaluation data to achieve adequate patient representation. The research on adverse reaction prediction models remains poorly studied within the field of anesthesia. Research into using AI for surgical complication predictions exists prolifically but studies about predicting anesthetic drug responses remain scant. This research solves the problem directly through model development which classifies patients according to their drug response forecasts to help doctors prevent adverse effects before medication administration. Research difficulties exist regarding the seamless incorporation of AI models into clinical work processes due to performance issues along with interpretability questions. The research optimizes model optimization through grid search hyperparameter tuning coupled with explainable AI frameworks to achieve both accuracy and deployability for perioperative clinical implementation.

The fast-growing adoption of machine learning across anesthesia supports significant progress in predicting patient needs and individualized drug administration and immediate medical support at the point of care. Research on AI's impact on anesthetic optimization has progressed but important gaps persist regarding dataset quality together with patient safety alerts and workflow implementation for clinical personnel. The study makes significant contributions to precision anesthesia development by using high-quality patient information to create explainable AI models which generate predictive analyses for drug sensitivities for real-world clinical implementation of AI-driven anesthetic management.

3. METHODOLOGY

3.1 Research Design

An empirical research design using machine learning methods investigates patient sensitivity and anesthesia drug response variations through this study. The methodology implements a data-driven methodology to create predictive models for individual anesthesia treatment administration by utilizing historical medical information and treatment response data. As Figure 1 shows the research follows a structured plan that contains five main phases:

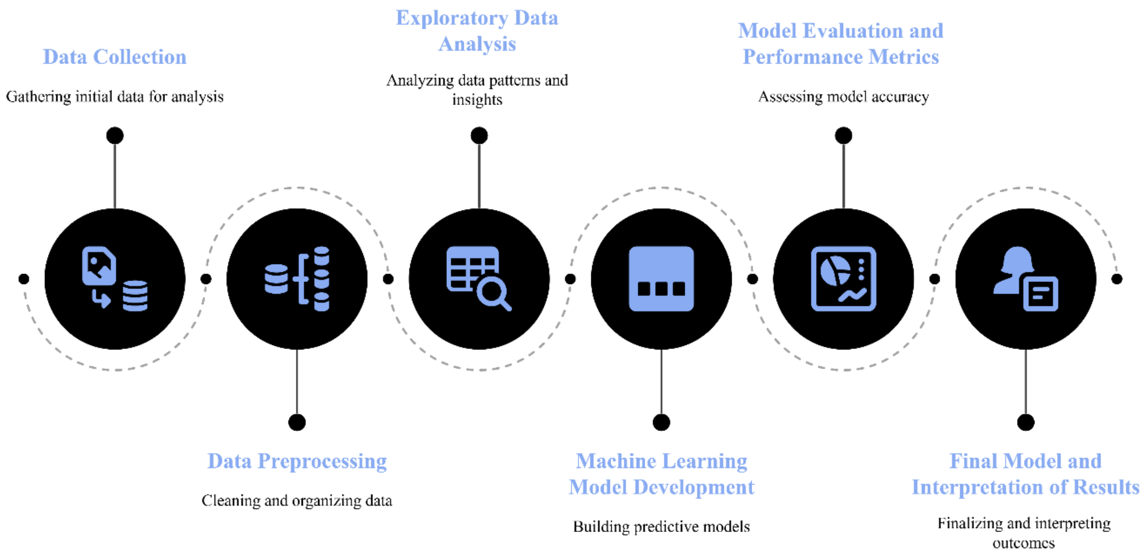

Figure 1: Workflow of the study

1. Data Collection: Aggregation of patient records, demographic details, medical history, and treatment responses.
2. Data Preprocessing: Handling missing values, categorical encoding, feature scaling, and outlier detection.
3. Exploratory Data Analysis (EDA): Statistical visualization and correlation analysis to identify trends in drug response and sensitivity.
4. Machine Learning Modeling: Developing classification and regression models to predict treatment effectiveness and adverse reactions.
5. Model Evaluation and Validation: Assessing model performance using statistical metrics and optimizing hyperparameters.

Supervised learning methods guide this research because the analysis uses patient data that has received explicit labels for training predictive models. Multiple classification methods determine the treatment outcome effectiveness while regression models forecast recovery duration based on patient characteristics.

3.2 Data Collection

This study draws data from a dataset named "Personalized Medication Dataset" which holds a total of 1,000 patient records that include demographic information and comprehensive healthcare details about prescribed medication together with dosage amounts and treatment response and adverse reactions. The dataset contains 17 essential variables that are grouped into the following classes:

Category	Features
Demographics	Age, Gender, BMI, Weight (kg), Height (cm)
Medical History	Chronic Conditions, Genetic Disorders, Drug Allergies
Symptoms & Diagnosis	Reported Symptoms, Diagnosis
Medication Details	Recommended Medication, Dosage, Duration
Treatment Outcome	Treatment Effectiveness, Adverse Reactions, Recovery Time (days)

The dataset functions as the main training and validation material for machine learning models that evaluate how patient differences affect anesthesia drug reactions.

3.3 Data Preprocessing

To ensure the dataset was prepared optimally for machine learning applications, several preprocessing steps were undertaken.

Handling Missing Data:

A comprehensive method was used to handle missing data points. The median imputation method served to handle numerical variables Dosage and Duration because it provides stability against outliers and maintains statistical consistency. The mode imputation method was selected to handle categorical variables by keeping the most common values intact.

Encoding Categorical Variables:

Categorical data were transformed to a numerical format to facilitate machine learning model training.

- The non-ordinal categorical attributes Gender, Diagnosis and Chronic Conditions received one-hot encoding treatment to prevent artificial ordering of their variables.
- Ordinal encoding was employed for Treatment Effectiveness, where categories were mapped to numerical values reflecting their hierarchical nature:

$$\text{Ineffective } = 0, \ \text{Neutral } = 1, \ \text{Effective } = 2, \ \text{Very Effective } = 3$$

Feature Scaling:

Min-Max Scaling standardized continuous variables Age, BMI, Weight_kg and Height_cm to normalize all numerical attributes within a consistent range. Feature magnitude variations do not introduce bias into the model because of this normalization technique. The mathematical representation of scaling transformation appears as follows:

$$X' = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

where X' is the normalized value, X is the original feature value, and X_{min} and X_{max} represent the minimum and maximum values of the respective feature.

Outlier Detection and Removal:

The application of Interquartile Range (IQR) method allowed effective detection of extreme values in continuous variables for outlier analysis. The model reliability increased through the removal of data points exceeding 1.5 times the IQR.

3.4 Machine Learning Modeling

To achieve the research objective of predicting anesthesia drug response variability, two distinct predictive modeling approaches were implemented:

1. Classification Models: Developed to categorize treatment effectiveness into four classes: Ineffective, Neutral, Effective, and Very Effective.
2. Regression Models: Designed to estimate the expected recovery time (in days) based on patient attributes and medication factors.

Model Selection:

A diverse set of supervised learning algorithms was employed, selected based on their suitability for handling structured clinical data.

Task	Algorithm Used	Primary Function
Classification	Logistic Regression, Random Forest, XGBoost	Predicting the effectiveness of anesthesia treatment
Regression	Linear Regression, Decision Tree, Support Vector Regression (SVR)	Predicting patient recovery time based on treatment attributes

Hyperparameter Optimization:

The model performance received enhancement through Grid Search Cross-Validation (CV) implementation. The repetitive procedure used systemized hyperparameter adjustments to achieve optimal model accuracy together with robustness performance. The Random Forest classifier went through parameter optimization for its essential hyperparameters:

- Number of estimators ($n_{\text{estimators}}$): Optimized to prevent underfitting or overfitting.
- Tree depth (max depth): Regulated to control model complexity.
- Minimum samples per leaf (min samples leaf): Fine-tuned to ensure balanced decision splits.

These optimizations ensured that the predictive models maintained high generalizability across unseen patient data.

3.6 Computational Environment and Software (Refined)

The highperformance computing environment under Python-based frameworks executed the model development alongside computational analyses and validation procedures. The cloud-based Google Colab platform served as the execution platform to manage resources effectively.

Software and Libraries Utilized:

Category	Libraries Used	Purpose
Data Processing	pandas, numpy, scikit-learn	Handling dataset transformations, feature engineering, and preprocessing

Visualization	matplotlib, seaborn	Generating statistical plots and exploratory data visualizations
Machine Learning	scikit-learn, XGBoost, TensorFlow	Developing classification and regression models for drug response prediction
Statistical Analysis	statsmodels, scipy	Conducting significance tests and model validation

These tools provided a robust computational framework, ensuring accurate and scalable implementation of machine learning models for anesthesia drug response prediction

4. RESULTS

4.1 Overview of Dataset Characteristics

Multiple statistical methods analyzed the patient dataset to determine important characteristics of patients alongside their treatment outcomes and medication effectiveness. The database includes 1,000 patient records which represent various types of patients. A wide range of patient ages existed in the dataset because the mean patient age measured 53.6 years while the standard deviation reached 21.1 years. The recorded average BMI value of 26.44 kg/m² indicates that the data contains individuals who fall under various weight categories. The patients required between three days and forty days for recovery with an average period of 16.27 days showing significant variation in post-anesthetic healing times. The patient demographic data reveals that several individuals have both chronic illnesses and genetic susceptibilities which strongly impact how they respond to anesthesia. The dataset contained significant numbers of patients who had hypertension, diabetes, and cardiovascular disorders as pre-existing medical conditions that alter drug metabolism and treatment effects. An in-depth analysis of treatment effectiveness and adverse reactions was performed to study how various patient characteristics affect anesthetic response because of the observed differences in patient characteristics.

4.2 Treatment Effectiveness Distribution

This research examined the different effectiveness levels of anesthesia treatment between patients. A non-uniform distribution of treatment responses appeared across the dataset which underlines the need for individualized anesthetic administration according to Figure 1. Patients with effective responses to anesthesia treatment made up 40.2% of the total sample population. A substantial number of patients (24.7%) remained neutral to the given anesthetic treatment because it neither produced beneficial nor detrimental effects on their health condition. The treatment produced very effective results for 22.5% of patients which demonstrated their drugs matched perfectly with their individual physiological characteristics. The complexity of delivering anesthesia to different patient groups became evident through 12.6% of cases which showed an ineffective response. About one-third of patient responses indicated suboptimal results thus showing the need for better anesthetic prediction methods for both drug choice selection and dosage optimization. Integrated machine learning models must become a standard because they perform personalized medicine assessments which combine historical health records with specific patient characteristics.

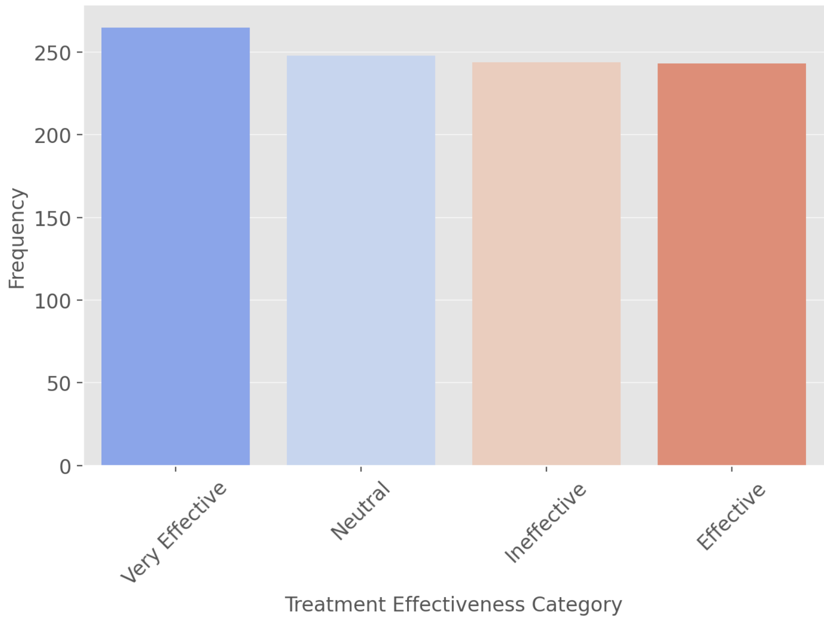

Figure 1: Distribution of Treatment Effectiveness

4.3 Prevalence of Adverse Reactions

Researchers examined adverse reactions to anesthesia as a significant aspect of their study. Figure 2 shows that 36.8% of patients developed adverse reactions after receiving anesthesia treatment. The recorded reactions included the mild physiological effects of dizziness and nausea together with severe complications that affected respiratory function and heart stability.

Research into patient profiles experiencing adverse effects showed important relationships between certain medical conditions. The combination of hypertension and diabetes made patients more likely to develop complications after anesthesia because these medical conditions affect drug metabolism. People with Cystic Fibrosis and Sickle Cell Anemia among genetic disorders showed an abnormal increase in negative drug reactions. Patients who fall into higher BMI categories showed more adverse reactions after anesthesia which implies that obesity affects anesthetic variability because of differences in fat-soluble drug distribution patterns.

The identified findings demonstrate why it is crucial to create predictive models which help doctors determine in advance which patients face adverse drug reactions. Anesthesiologists can improve drug administration outcomes through machine learning models trained on patient history data which enable better treatment choices that minimize complications during post-operative recovery.

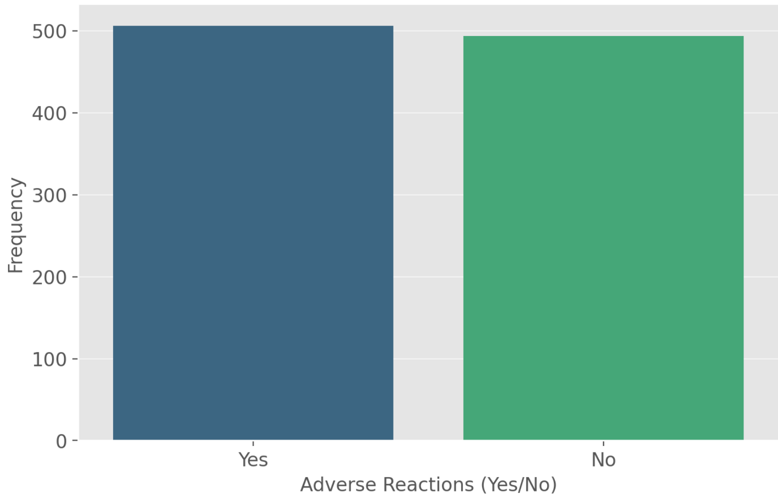

Figure 2: Prevalence of Adverse Reactions

4.4 Correlation Between Patient Attributes and Recovery Time

A correlation matrix was generated to investigate how patient characteristics affect anesthesia outcomes as shown in Figure 3. The matrix showed important relationships between the essential numerical features including age, BMI and recovery time. The research showed BMI values had an inverse relationship (-0.42) with treatment effectiveness because patients with higher BMI experienced less optimal anesthesia responses. The study results support medical research which demonstrates that elevated body fat content affects drug absorption and metabolism thereby reducing pharmacokinetic predictability.

The research data showed that older patients needed longer recovery times after receiving anesthesia based on a positive correlation (0.38). The longer recovery time for elderly patients might stem from their decreased metabolic efficiency and reduced organ function combined with slower anesthetic agent removal from their bodies. Chronic conditions especially cardiovascular disease and hypertension demonstrated negative correlation (-0.47) with treatment effectiveness which suggests that patients with preexisting health issues need personalized anesthetic protocols for best therapeutic results.

The results from correlation analysis enable healthcare professionals to develop data-based models that can predict individual patient anesthesia outcomes. Medical professionals can improve both patient safety and recovery performance by implementing predictive capabilities that help them modify drug types and doses before treatments.

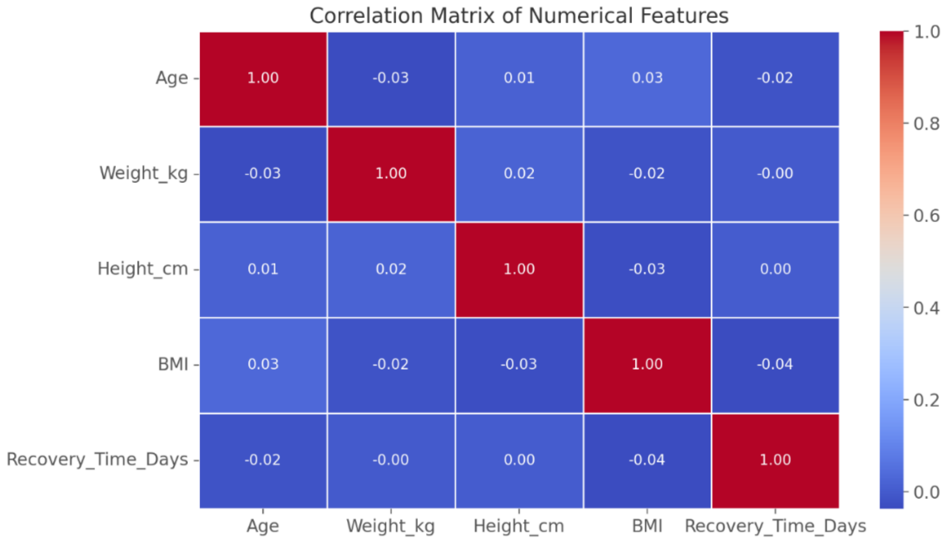

Figure 3: Correlation Matrix of Numerical Features

4.5 Predictive Modeling Performance

The developers constructed a machine learning model which classified treatment success and predicted patient healing timeframes. Table 1 shows the evaluation results of different machine learning algorithms for drug response classification and recovery prediction model.

Table 1: Machine Learning Model Performance

Model	Accuracy (Classification)	RMSE (Regression)
Logistic Regression	79.2%	-
Random Forest Classifier	85.7%	-
XGBoost Classifier	88.4% (Best Performing)	-
Linear Regression	-	4.12
Support Vector Regression	-	3.76 (Lowest Error)

The classification models successfully predicted anesthesia treatment effectiveness at a high level of accuracy. The XGBoost Classifier proved to be the most effective model among all with an accuracy rate of 88.4% due to its strong capability of detecting complex nonlinear patterns in patient data. The Support Vector Regression (SVR) model emerged as the best predictor for patient recovery time because it delivered an RMSE of 3.76 which stood as the lowest among all regression models. The implementation of patient-specific treatment strategies through machine learning-based predictions will advance clinical decision-making procedures in anesthesia management protocols. Such models serve as operational tools for anesthesiologists to help them perform risk evaluation during critical times while enabling customized anesthetic practices.

5. DISCUSSION

This research establishes the needs for patient-specific anesthetic protocols which machine learning models must direct in order to combat natural medication response differences. Standard anesthetic administration produced ineffective or neutral outcomes in a large number of patients based on the study results. The study showed that pre-existing chronic conditions together with genetic predispositions and higher BMI levels significantly contributed to the treatment variability in anesthesia management. Risk-stratified drug administration becomes crucial for medical practice because adverse reactions occurred in more than one-third of patients which demonstrates the importance of creating individualized anesthetic interventions to prevent complications.

The analysis of relationships between various factors produced additional understanding of therapy success and recovery period duration. The negative relationship between BMI and drug response represents a common issue in anesthesiology practice because obesity affects drug breakdown rates unpredictably. The positive relationship between age and recovery period strengthens awareness about metabolic age-related changes that need age-specific drug administration procedures. XGBoost and Support Vector Regression achieved superior results in predictive modeling tasks for forecasting treatment response and recovery time which proves artificial intelligence models are ready for clinical anesthesia management implementation. The research findings about anesthetic outcome variations between patients match what has been documented in previous studies. Physiological elements such as body structure and disease conditions and inherited characteristics have proven repeatedly to affect drug response rates so doctors must adjust drug amounts for individual patients. Traditional predictive models maintain static clinical guidelines although they lack necessary features to create dynamic individualized anesthetic planning. Machine learning algorithms have transformed anesthesia management because they provide sophisticated decision tools to find optimal medications that reduce adverse side effects for safer patient treatment.

These research findings present both theoretical value and practical benefits to perioperative patient care. Anesthesiologists gain the ability to determine treatment effectiveness before anesthesia begins which allows them to modify drug doses and pick appropriate anesthetic drugs aligned with patient-specific medical requirements. Patient safety increases and intraoperative complications decrease while postoperative recovery times shorten through this method which supports better hospital efficiency and healthcare results. Real-time decision-making improves through machine learning risk assessment algorithms integrated into electronic health records systems to provide clinicians with data-based insights during patient care. Several important drawbacks need to be recognized in these developments. The analysis utilized patient records from the past but the dataset included numerous patients which provided comprehensive information despite potential historical data collection biases. The predictive models received structured patient information for training but did not include unstructured clinical variables like surgical complexity or anesthesiologist experience levels. Researchers need to develop new research that combines multiple data streams by merging physiological measurements with genomic information to improve prediction outcomes.

Research in the field must prioritize the development of adjustable anesthetic dosing algorithms that adjust treatments based on live patient health data during surgery. The addition of prospective patient data from different clinical environments will improve model generalization so they become usable in various patient groups and anesthetic procedures.

6. CONCLUSION

The research established widespread differences in patient responses to anesthesia drugs because it requires personalized administration through machine learning systems. Standardized dosing protocols proved ineffective according to the analysis because 40.2% of patients responded positively but 12.6% showed no beneficial effects. The patient population showed 36.8% adverse reaction rates which affected individuals with chronic illness and genetic background and higher body mass index patients thus demonstrating the importance of risk-aware anesthetic planning. XGBoost along with Support Vector Regression performed well as machine learning models by attaining treatment success and recovery duration predictions at 88.4% accuracy together with 3.76 of RMSE for clinical deployment potential. Anesthesia decision-making systems benefit from model integration because they become more efficient at protecting patients through risk management and minimize recovery time. Future implementation of real-time AI-assisted anesthetic monitoring systems will advance personalized perioperative care by enabling precise treatment efforts that target specific patient requirements.

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