Archives of Anesthesiology and Critical Care (In Press); x(x): xx-xx.

Available online at http://aacc.tums.ac.ir

Research Article

Machine Learning–Based Prediction of Hemodynamic Instability after Spinal Anesthesia

Atiyeh Sadat Sajadi[1], Mehrdad Mesbah Kiaei[2], Rahele Charmchi[1], Zeinab Barzegar[3], Kimia Khonakdar[4], Shahnam Sedigh Maroufi[1], Mahsa Atri Roozbahani[5], Parisa Moradimajd[1]*

[1]Department of Anesthesia, School of Allied Medical Sciences, Iran University of Medical Sciences, Tehran, Iran.

[2]Department of Anesthesiology and Pain Medicine, School of Medicine, Hasheminejad Kidney Center, Iran University of Medical Science, Tehran, Iran.

[3]Department of Artificial Intelligence in Medicine, Faculty of Advanced Technologies in Medicine, Iran University of Medical Science, Tehran, Iran.

[4]Department of Anesthesiology, School of Allied Medical Sciences, Mazandaran University of Medical Sciences, Sari, Iran.

[5]Department of Anesthesiology, Mohebe Kosar Hospital, Faculty of Medicine, Iran University of Medical Sciences, Tehran, Iran.

ARTICLE INFO

Article history:
Received 16 February 2026
Revised 10 March 2026
Accepted 23 March 2026

Keywords:
Anesthesia;
Spinal;
Hypotension;
Postoperative Nausea and Vomiting;
Heart Rate;
Urologic Surgery;
Machine Learning;
Artificial Intelligence

ABSTRACT

Background: Hypotension, heart rate changes, and postoperative nausea and vomiting (PONV) are common complications of spinal anesthesia in urologic surgeries, which may lead to hemodynamic instability, increased therapeutic interventions, and reduced patient satisfaction. Early identification of high-risk patients can play a crucial role in the prevention and management of these complications.

Methods: In this study, data from patients undergoing urologic surgeries under spinal anesthesia were collected, cleaned, and preprocessed. Various machine learning models, including logistic regression, support vector machine, decision tree, random forest, and multilayer perceptron (MLP) neural networks, were trained to predict hypotension, heart rate changes, and PONV. Feature selection was performed using the Boruta algorithm and correlation analysis.

Results: The MLP model achieved the strongest predictive performance for hypotension (AUC ≈ 0.86), heart rate changes (AUC ≈ 0.91), and PONV (AUC ≈ 0.87–0.90). The most important predictors were baseline blood pressure and heart rate, ASA status, age, surgical type and duration, and intraoperative medication use.

Conclusion: Machine learning models may be useful for identifying patients at high risk before complications develop after spinal anesthesia, offering a basis for building clinical decision support systems.

Introduction

The expansion of local anesthesia techniques began with the discovery of cocaine, and the first local anesthesia technique, namely spinal anesthesia (S.A.), was first introduced and performed in Germany in 1898 [1]. Since then, this method has been used as one of the most common and widely applied regional anesthesia techniques in surgeries of the lower body. The major advantages of spinal anesthesia include no need for airway manipulation, reduced complications related to general anesthetic drugs, adequate postoperative analgesia, and, consequently, reduced opioid

The authors declare no conflicts of interest.

*Corresponding author.
E-mail address: moradimajd.p@gmail.com

DOI:

consumption. These features have made the S.A. technique highly popular across a wide range of surgeries, including orthopedic procedures; gynecological surgeries such as cesarean sections; and especially urologic surgeries [2]. Spinal anesthesia is highly effective for urologic surgeries because they are often short-term, elective, and restricted to the pelvic and perineal areas. Common examples include inguinal hernia repair, TURP, and ureteral lithotripsy [3].

Despite its numerous benefits, spinal anesthesia, like other anesthetic methods, is associated with complications, the most common and significant of which is hypotension. This complication, known as spinal anesthesia–induced hypotension (SAIH), has an incidence of up to approximately 75% [4]. The primary mechanism of SAIH involves sympathetic blockade, arterial and venous vasodilation, decreased systemic vascular resistance, and reduced stroke volume, ultimately leading to hemodynamic instability [5-6].

Hypotension following spinal anesthesia can result in multiple clinical consequences. Reduced preload and Bezold–Jarisch reflex activation are among the mechanisms that, through stimulation of serotonergic receptors and the chemoreceptor trigger zone (CTZ) in the central nervous system, can cause nausea and vomiting. Additionally, decreased visceral blood flow, particularly a reduction in splenic perfusion by approximately 20%, may increase the production of emetogenic substances from the gastrointestinal tract [7]. Other significant complications of SAIH include reduced cerebral perfusion, decreased oxygen saturation in brain cells, dizziness, and decreased consciousness, which in severe cases can lead to cerebral ischemia [8]. Evidence indicates that morbidity, mortality, and hospital length of stay are up to 20% higher in patients experiencing hypotension during anesthesia or spinal anesthesia compared to other patients [9].

Several factors are associated with the development of hypotension after spinal anesthesia, including patient age, weight, and height; ASA physical status; surgical duration; a history of conditions such as acute kidney injury or myocardial infarction; the type and dose of the local anesthetic; preoperative fluid administration; achieving a sensory block at T5 or higher; intraoperative opioid use; and the use of antihypertensive medications before surgery [10]. Given the high workload in operating rooms, simultaneous performance of multiple surgeries, and lack of adherence to the recommended ratio of anesthesiologists to operating rooms, predicting hypotension in many patients is challenging or even impossible for the anesthesia team [10]. Therefore, the need for precise and reliable tools to identify high-risk patients early is increasingly recognized. In recent years, artificial intelligence (AI) has assumed an increasingly important role in a wide range of domains, particularly medicine and healthcare [11-12]. A major component of AI is machine learning (ML), which employs advanced statistical algorithms to detect complex patterns and nonlinear relationships within medical data [13-14]. In medicine, ML has been applied to tasks such as disease prediction, diagnosis, survival and mortality estimation, biosignal analysis, and medical image processing [15-17]. A variety of ML techniques, including logistic regression, support vector machines, decision trees, random forests, artificial neural networks, and Naïve Bayes, offer distinct advantages for modeling clinical data and predicting medical outcomes [18-22]. One key advantage shared by these approaches is their capacity to reveal hidden and nonlinear associations among variables. Considering the high prevalence of spinal anesthesia use in urologic surgeries, the frequent occurrence of hypotension and its undesirable consequences, and the practical limitations in the operating room environment, this study was designed to investigate the capability of ML algorithms in predicting hypotension following spinal anesthesia in patients undergoing urologic surgeries.

Methods

Study Design

This research is a retrospective observational analytical study aimed at predicting hypotension after spinal anesthesia in patients undergoing urologic surgeries using ML algorithms. Patient sampling commenced following approval from the Ethics Committee (IR.IUMS.REC.1403.546).

Study Population and Sample

The study population comprised all patients who underwent urologic surgeries under spinal anesthesia in the operating rooms of Hasheminejad Hospital. A census sampling approach was employed. According to the common rule of thumb for machine learning models, which recommends a minimum of ten times the number of predictor variables, and considering the inclusion of 29 predictors, the required minimum sample size was estimated at 290 patients. Ultimately, data from 300 eligible patients were incorporated into the final analysis.

Inclusion and Exclusion Criteria

Inclusion criteria comprised patients aged 18–65 years undergoing urologic surgery under spinal anesthesia. Exclusion criteria included dialysis patients and patients with acute kidney injury (AKI).

Variables and Data Collection Tools

Patient data were retrospectively extracted from medical records. The data collection tool was a researcher-made checklist of risk factors affecting hypotension following spinal anesthesia, developed based on a literature review, recent articles, reliable evidence, and expert anesthesiologist interviews.

A total of 29 risk factors were included in the modeling, including age, sex, height, weight, ASA classification, comorbidities, smoking status, history of hypotension, motion sickness, neurological diseases, previous spinal anesthesia, type of surgery (elective or emergency), needle size and type, spinal technique (median or paramedian), local anesthetic drug type, volume and rate of injection, number of attempts, puncture site, surgery duration, anesthesia duration, blood loss, opioid use, beta-blocker or calcium channel blocker use, antibiotic use, body temperature, operating room temperature, pain severity, fluid type, and fluid therapy volume.

Outcome Definition

The primary outcome was hypotension following spinal anesthesia, defined as a binary variable (occurrence or non-occurrence). Patients' blood pressure was recorded before injection of the anesthetic and measured every 3 minutes for 15 minutes post-injection.

Data Preprocessing

Prior to input into ML models, preprocessing involved data cleaning, identification and correction of inconsistent data, management of missing values using appropriate statistical methods, normalization or standardization of numerical variables, and encoding of categorical variables using methods such as one-hot encoding. In cases of class imbalance, SMOTE or class weighting was applied. Dimensionality reduction using PCA or feature selection was performed if necessary.

Data Splitting

The dataset was randomly divided into training (70%), validation (15%), and test (15%) subsets while preserving class distribution. The training set was used to develop the models, the validation set to optimize hyperparameters, and the test set to assess final model performance.

Feature Selection

To avoid data leakage, feature selection was conducted only on the training set. Embedded approaches, such as the Boruta algorithm, as well as regularization-based methods including LASSO and Elastic Net, were applied. The selected features were then used unchanged in the validation and test sets.

Modeling and Data Analysis

Machine learning techniques, including logistic regression, Naïve Bayes, random forest, and artificial neural networks (ANNs), were used for data analysis. The task was formulated as a binary classification problem. Python served as the programming language, and standard machine learning libraries were used to implement the models.

Hyperparameter Tuning and Model Evaluation

Hyperparameters were optimized using Grid Search and Random Search combined with k-fold cross-validation. Model performance was assessed with the confusion matrix, accuracy, precision, recall, sensitivity, F1 score, and AUC.

Results

In this study, after preprocessing steps such as data cleaning, handling missing values, normalizing numerical variables, and encoding categorical variables, data from patients who underwent urologic surgeries under spinal anesthesia were analyzed. Results are presented based on study objectives and dependent variables, including hypotension, heart rate changes, and postoperative nausea and vomiting (PONV).

Prediction of Hypotension after Spinal Anesthesia

Following feature selection using the Boruta algorithm, a set of clinical and hemodynamic variables were identified as the most important predictors of hypotension after spinal anesthesia. These predictors consisted of baseline blood pressure, ASA physical status, patient age, surgical type, operative duration, and the administration of intraoperative vasoactive medications. Upon evaluating various machine learning algorithms, the MLP neural network demonstrated superior accuracy in forecasting hypotension. It achieved an AUC and F1-score of roughly 0.86, indicating a strong equilibrium between sensitivity and specificity. While alternative models like logistic regression, support vector machines (SVM), decision trees, and random forests yielded acceptable results, their performance metrics fell short of the MLP.

Prediction of Heart Rate Changes

When evaluating heart rate variations, such as clinically relevant tachycardia or bradycardia, the application of Boruta-based feature selection notably enhanced the predictive capabilities of all models. Consistent with previous results, the MLP model demonstrated superior efficacy, yielding an AUC of roughly 0.91 and an F1-score near 0.90.

The most important predictors of heart rate changes included baseline heart rate, intraoperative blood pressure changes, type and dose of anesthetic and vasoactive drugs, and surgery duration. These findings suggest that nonlinear models, particularly neural networks, are highly capable of identifying complex hemodynamic patterns in patients under spinal anesthesia.

Prediction of Postoperative Nausea and Vomiting (PONV)

In predicting PONV, all examined ML models showed acceptable performance. Using the Boruta feature selection approach, AUC and F1-score values for random forest, SVM, logistic regression, and MLP models were mostly in the range of 0.87–0.90.

The primary factors identified for predicting PONV encompassed patient sex, a prior history of post-anesthesia nausea and vomiting or motion sickness, opioid administration, duration of the surgical procedure, smoking history, type of fluid administered, and the intensity of postoperative pain. Combining these variables with hemodynamic indices improved the models' accuracy in identifying patients at risk of PONV.

Discussion

The results of this study showed that ML models, particularly the MLP neural network, outperform traditional methods in predicting complications following spinal anesthesia. These findings are consistent with evidence from international and domestic studies.

Studies by Tully et al. (2023) and Bishara et al. (2022) demonstrated that ML models such as XGBoost and ANN have higher predictive capability than logistic regression for postoperative or post-anesthesia outcomes (AUC ~0.84–0.85), which aligns with our results, where MLP achieved the highest AUC (0.86) and F1-score (0.86) for hypotension prediction [23-24].

Consistent with our results for predicting PONV, Bellini et al. (2022) also demonstrated that nonlinear models like random forest and gradient boosting are more effective at predicting postoperative outcomes [25].

In previous domestic studies, such as Mehrad et al. (2022) and Abedini et al. (2020), ANN demonstrated superior performance and remarkable accuracy relative to alternative algorithms. This underscores the proficiency of nonlinear models in processing intricate clinical data, even when constrained by a limited sample size.

These findings are consistent with our observation that Boruta-based feature selection reduced data noise and improved predictive accuracy [26-27].

Despite similarities, some differences were noted. For example, Lee et al. (2020) demonstrated that a MLP outperformed a CNN model in predicting hypotension following anesthesia induction, whereas Solam Lee et al. (2021) showed that combining biosignal data improved deep learning models' performance [28]. Such differences may relate to data type, population characteristics, data collection timeframe, and variable selection.

Our findings indicate that MLP neural networks can identify complex hemodynamic patterns in patients under spinal anesthesia and may serve as an auxiliary tool for clinical decision-making in predicting hypotension, heart rate changes, and PONV.

Limitations

Because this research relied on the real clinical data of a small cohort of urology patients undergoing surgery, its findings may not readily apply to broader populations or different surgical specialties. Furthermore, to ensure their practical effectiveness in clinical settings, the machine learning models must undergo external validation and real-world trials.

Suggestions for Future Research

Future research should focus on incorporating multicenter datasets, integrating physiological and clinical data, and conducting real-time testing to enhance the precision and clinical utility of machine learning models. Furthermore, investigating sophisticated deep learning architectures, like CNNs and LSTMs, offers a promising avenue for predicting complications in real time.

Conclusion

This study demonstrates that machine learning algorithms, particularly the MLP model, possess significant predictive capabilities for post-spinal anesthesia complications in patients undergoing urological surgery. The model's robust performance in forecasting hypotension, heart rate fluctuations, and postoperative nausea and vomiting (PONV) highlights its potential as an effective tool for the early identification of high-risk patients. Our findings further indicate that baseline blood pressure and heart rate, ASA physical status, age, and type of surgery are the most critical predictors. Consequently, the integration of machine learning models into clinical practice can play a pivotal role in enhancing clinical decision-making, improving patient safety, and optimizing perioperative management.

References

[1] Bembenick KN, Nguyen A, Jackson C, Shekoohi S, Kaye AJ, Kaye AD, et al. Neuraxial anesthesia for vaginal delivery. In: Pharmacology, physiology, and practice in obstetric anesthesia. Elsevier; 2025;163-73.

[2] Stewart J, Gasanova I, Joshi GP. Spinal anesthesia for ambulatory surgery: current controversies and concerns. Curr Opin Anesthesiol. 2020; 33(6):746-52.

[3] Ebert KM, Jayanthi VR, Alpert SA, Ching CB, DaJusta DG, Fuchs ME, et al. Benefits of spinal anesthesia for urologic surgery in the youngest of patients. J Pediatr Urol. 2019; 15(1):49.e1-49.e6.

[4] Šklebar I, Bujas T, Habek D. Spinal anaesthesia-induced hypotension in obstetrics: prevention and

therapy. Acta Clin Croat. 2019; 58(Suppl 1):90-5.
[5] Hofhuizen C, Lemson J, Snoeck M, Scheffer G-J. Spinal anesthesia-induced hypotension is caused by a decrease in stroke volume in elderly patients. Local Reg Anesth. 2019; 12:19-26.
[6] Ferré F, Martin C, Bosch L, Kurrek M, Lairez O, Minville V. Control of spinal anesthesia-induced hypotension in adults. Local Reg Anesth. 2020; 13:39-46.
[7] Ju JW, Kwon J, Yoo S, Lee HJ. Retrospective analysis of the incidence and predictors of postoperative nausea and vomiting after orthopedic surgery under spinal anesthesia. Korean J Anesthesiol. 2023; 76(2):99-106.
[8] Shitemaw T, Jemal B, Mamo T, Akalu L. Incidence and associated factors for hypotension after spinal anesthesia during cesarean section at Gandhi Memorial Hospital Addis Ababa, Ethiopia. PLoS One. 2020; 15(8):e0236755.
[9] Kang AR, Lee J, Jung W, Lee M, Park SY, Woo J, et al. Development of a prediction model for hypotension after induction of anesthesia using machine learning. PLoS One. 2020; 15(4):e0231172.
[10] Chumpathong S, Chinachoti T, Visalyaputra S, Himmunngan T. Incidence and risk factors of hypotension during spinal anesthesia for cesarean section at Siriraj Hospital. J Med Assoc Thai. 2006; 89(10):1804.
[11] Trolice MP, Curchoe C, Quaas AM. Artificial intelligence-the future is now. J Assist Reprod Genet. 2021; 38(7):1607-12.
[12] Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism. 2017; 69:S36-S40.
[13] El Naqa I, Murphy MJ. What is machine learning? In: Machine learning in radiation oncology: theory and applications. Springer; 2015;3-11.
[14] Mackenzie A. The production of prediction: What does machine learning want? Eur J Cult Stud. 2015; 18(4-5):429-45.
[15] Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med. 2019; 380(14):1347-58.
[16] Ray S. 2019 international conference on machine learning, big data, cloud and parallel computing (COMITCon). IEEE; 2019;35-39.
[17] Christodoulou E, Ma J, Collins GS, Steyerberg EW, Verbakel JY, Van Calster B. A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. J Clin Epidemiol. 2019; 110:12-22.
[18] Bisong E. Building machine learning and deep learning models on Google cloud platform. Springer; 2019.
[19] Schonlau M, Zou RY. The random forest algorithm for statistical learning. Stata J. 2020; 20(1):3-29.
[20] Devika R, Avilala SV, Subramaniyaswamy V. Comparative study of classifier for chronic kidney disease prediction using naive bayes, KNN and random forest. In: 2019 3rd International conference on computing methodologies and communication (ICCMC). IEEE; 2019;679-84.
[21] Amato F, López A, Peña-Méndez EM, Vaňhara P, Hampl A, Havel J. Artificial neural networks in medical diagnosis. J Appl Biomed. 2013; 11(2):47-58.
[22] Shanmuganathan S. Artificial neural network modelling: An introduction. In: Artificial neural network modelling. Springer; 2016;1-14.
[23] Tully JL, Zhong W, Simpson S, Curran BP, Macias AA, Waterman RS, et al. Machine learning prediction models to reduce length of stay at ambulatory surgery centers through case resequencing. J Med Syst. 2023; 47(1):71.
[24] Bellini V, Valente M, Bertorelli G, Pifferi B, Craca M, Mordonini M, et al. Machine learning in perioperative medicine: a systematic review. J Anesth Analg Crit Care. 2022; 2(1):2.
[25] Bishara A, Chiu C, Whitlock EL, Douglas VC, Lee S, Butte AJ, et al. Postoperative delirium prediction using machine learning models and preoperative electronic health record data. BMC Anesthesiol. 2022; 22(1):8.
[26] Mehrad M, Nojavan M, Raissi S, Javadi M. A two-stage approach using artificial neural networks for diagnosis of heart diseases based on ECG data. J Arak Univ Med Sci. 2022; 25(2):230-43.
[27] Abedini A, Jabarpour E, Keshtkar A. Predicting the risk of osteoporosis using decision tree and neural network. J Health Biomed Inform. 2020; 7(3):304-17.
[28] Lee J, Woo J, Kang AR, Jeong Y-S, Jung W, Lee M, et al. Comparative analysis on machine learning and deep learning to predict post-induction hypotension. Sensors. 2020; 20(16):4575.