Kocatepe Tıp Dergisi
Kocatepe Medical Journal
27:42-48/ Ocak 2026 Sayısı

ARAŞTIRMA YAZISI / RESEARCH ARTICLE

KARDİYOVASKÜLER CERRAHİDE ERITROSİT İHTİYACINI TAHMİN ETMEK İÇİN MAKİNE ÖĞRENMESİ İLE GELENEKSEL MODELLERİN KARŞILAŞTIRMALI ANALİZİ

COMPARATIVE ANALYSIS OF MACHINE LEARNING VERSUS CONVENTIONAL MODELS FOR PREDICTING ERYTHROCYTE NEED IN CARDIOVASCULAR SURGERY

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ÖZET

AMAÇ: Kardiyovasküler cerrahi sırasında aşırı kanama, hastalar için önemli riskler oluşturur ve optimal perioperatif yönetim için eritrosit süspansiyonu (ES) gereksinimlerinin doğru bir şekilde tahmin edilmesini gerektirir. Bu çalışma, koroner arter baypas greftleme (CABG) ameliyatları sırasında ES ihtiyaçlarını tahmin etmede makine öğrenimi (ML) algoritmalarının geleneksel puanlamalara karşı etkinliğini karşılaştırmayı amaçlamaktadır.

GEREÇ VE YÖNTEM: Hastaların demografik, ameliyat öncesi ve cerrahi verileri kullanılarak geliştirilen ML algoritması, altı bilinen kanama tahmin skoruyla karşılaştırıldı. ES ihtiyacı tahminleri lojistik regresyon tabanlı sinir ağları kullanılarak analiz edildi.

BULGULAR: İzole CABG ameliyatları geçiren toplam 430 hasta analize dahil edildi. ML algoritmaları, herhangi bir ES ihtiyacını tahmin etmede %75,5 ve >2 ünite ES ihtiyacını tahmin etmede %93,8 doğrulukla geleneksel puanlama sistemlerine benzer tahmin gücü gösterdi. Geleneksel puanlama sistemleri arasında, TRUST puanı en yüksek öngörü yeteneğini sergiledi, ardından TRACK ve WILL BLEED puanları geldi.

SONUÇ: ML algoritması, perioperatif planlamada kullanımını artırarak, yerel adaptasyon ve kendini iyileştirme potansiyeli gösterdi. Bulgularımız, kardiyovasküler cerrahide kan ürünü kullanımını optimize etmede ML algoritmalarının uygulanabilirliğini vurgulamaktadır. Bu modellerin çeşitli klinik ortamlarda ölçeklenebilirliğini ve genelleştirilebilirliğini keşfetmek için daha fazla araştırma yapılması gerekmektedir. CABG ameliyatından önce hastalarda ES transfüzyon hazırlığı için ML tahminleri, geleneksel puanlama sistemlerine kıyasla yüksek derecede doğruluk ve karşılaştırılabilir performans göstermektedir. ML algoritmalarının kendilerini yerel verilerle güçlendirme ve değişen klinik bağlamlara uyum sağlama yeteneği, zaman içinde öngörü doğruluğunu artırma potansiyellerini vurgulamaktadır.

ANAHTAR KELİMELER: Makine Öğrenmesi, Kardiyovasküler Cerrahi, Perioperatif Kanama, Eritrosit Transfüzyonu, Tahmini Modelleme.

ABSTRACT

OBJECTIVE: Excessive bleeding during cardiovascular surgery poses significant risks to patients, necessitating accurate prediction of erythrocyte suspension (ES) requirements for optimal perioperative management. This study aims to compare the efficacy of machine learning (ML) algorithms against conventional scorings in predicting ES needs during coronary artery bypass grafting (CABG) surgeries.

MATERIAL AND METHODS: The ML algorithm, developed using patient demographic, preoperative, and surgical data, was compared with six established bleeding prediction scores. ES need predictions were analyzed using logistic regression-based neural networks.

RESULTS: A total of 430 patients undergoing isolated CABG surgeries were included in the analysis. ML algorithms demonstrated comparable predictive power to conventional scoring systems, with an accuracy of 75.5% for predicting any ES need and 93.8% for predicting the need for >2 units of ES. Among traditional scoring systems, the TRUST score exhibited the highest predictive ability, followed by the TRACK and WILL BLEED scores.

CONCLUSIONS: The ML algorithm showed potential for local adaptation and self-improvement, enhancing its utility in perioperative planning. Our findings underscore the feasibility of ML algorithms in optimizing blood product utilization in cardiovascular surgery. Further research is warranted to explore the scalability and generalizability of these models across diverse clinical settings. ML predictions for ES transfusion readiness in patients prior to CABG surgery demonstrate a high degree of accuracy and comparable performance to traditional scoring systems. The ability of ML algorithms to reinforce themselves with local data and adapt to changing clinical contexts highlights their potential for enhancing predictive accuracy over time.

KEYWORDS: Machine Learning, Cardiovascular Surgery, Perioperative Bleeding, Erythrocyte Transfusion, Predictive Modeling.

Geliş Tarihi / Received: 24.01.2025
Kabul Tarihi / Accepted: 05.06.2025
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INTRODUCTION

Excessive bleeding during complex cardiovascular surgical procedures increases perioperative mortality and morbidity. Bleeding during cardiac surgery leads to the loss of coagulation factors and hemodilution. Some loss of erythrocytes is unavoidable, even if attempts are made to reuse bleeding areas by cardiac pump aspirators (1). In cardiac surgery, blood products are used in more than 50% of cases and are inversely proportional to outcomes (2). These products need to be prepared in advance and supplied as needed in the case of severe bleeding. However, hibernating an unnecessary number of products may result in discarding unused product. For these reasons, estimating and supplying the required blood products with high consistency is crucial for patient safety, cost-effectiveness, and efficient resource utilization.

Perioperative bleeding in cardiovascular surgery may be due to more than one factor. Many factors, such as the type of surgery, technique, experience of the team, and clinical condition of the patient, determine the amount of bleeding (3). Many scoring systems have been developed to estimate this amount of bleeding. The parameters used by these scoring systems are generally similar. However, there is no consensus on which scoring system is superior (4).

Machine learning (ML) algorithms can be used perioperatively in various areas, such as the measurement of the depth of anesthesia, risk estimation, facilitation of ultrasound-mediated procedures, early intervention in pain management, or logistics in the operating room (5,6). ML models can enable individualized preparations or plans for patients, based on clinicians or surgical teams, with support from guidelines and evidence. Supervised ML algorithms can predict the risk in subsequent patients by testing algorithms based on previous patient data (7).

Haver et al. used random forest to find similar patient groups. For each group, they trained a machine learning with ICU multi-sensor information and monitor patients' vital parameters and generate appropriate alarms. This resulted in a 98% reduction in false alarms. In another study, a hypotensive event that may occur in a patient could be detected 15 minutes earlier with a sensitivity of 95% (8). The creation of algorithms with ML, the benefits and risks in learning or decision-making mechanisms, and their adaptation to anesthesia equipment will be the subjects of much research.

The success of ML algorithms in predicting perioperative blood product use in CABG remains an under-tested topic. Unnecessary preparation of blood products or not being able to supply them when necessary is critical for both patient safety and the effective use of hospital resources (9). Bleeding amounts and blood product use strategies can vary with institute protocols. Scoring systems that determine the general framework may not perform well due to local factors. ML algorithms can be created locally according to previous patient data of each clinic and can improve themselves with learning mechanisms, suggesting significant potential in this field.

In the current study, a new estimation system created with the ML algorithm was compared with the known estimation systems. Comparing the ML algorithm with 6 different classical scoring systems is important in terms of demonstrating the potential of this technology.

The aim of this study is to investigate whether the model we created with ML in predicting perioperative blood product consumption in cardiovascular surgeries is superior to predictive scoring systems that have proven themselves in the literature. Our secondary aim is to compare the predictive value of using more than one scoring system in combination.

MATERIAL AND METHODS

The study was conducted at a tertiary research hospital with 1600 beds, specializing in complex cardiovascular surgeries. The centre performs an average of 500 coronary artery bypass grafting (CABG) and other heart surgeries annually.

Retrospective data from 430 patients were included in our study. Thirty patients were excluded based on exclusion criteria. Intraoperative ES consumption was compared using six different predictive scoring. Inclusion criteria consisted of patients undergoing isolated CABG surgery, with demographic and preoperative data (age, gender, body mass index (BMI), medication use, previous surgical history, comorbidities, etc.), and surgical data (operation type, operation duration, Cardiopulmonary bypass pump (CPB) duration) available in the records. Exclusion criteria included emergency surgeries, patients with missing data, valve surgeries, CABG with valve surgeries, and off-pump CABG surgeries.

Bleeding Scoring Systems

This study utilized the most commonly used bleeding prediction scores in the literature, including ACTION (10), ACTA-PORT (11), WILL BLEED (12), PAPWORTH (13), TRACK (14), TRUST (15), and CRUSADE (16) scores. Some of these scores were created for cardiovascular surgery and some for percutaneous interventions and are frequently used evaluations. These scores have been tested for predicting intraoperative and postoperative blood product requirements (10-15). The utilized scores and their included parameters are shown in **Table 1**.

Table 1: The scoring systems used in the study

NAME OF THE SCORING SYSTEM	DEFINITION	PARAMETERS INCLUDED	RISK CLASSIFICATION
ACTION	Acute Coronary Treatment and Intervention Outcomes Network	Age, basal serum creatinin, systolic blood pressure on admission, basal hemoglobin, pulse rate on admission, gender, body weight, warfarin usage, diabetes mellitus, heart failure or cardiogenic shock on admission, electrocardiographic changes, presence of peripheral arterial disease	0: ≤20 (very low risk), I: 21 - 30 (low risk), II: 31 - 40 (moderate risk), III: 41 to 50 (high risk) IV: ≥50 (very high risk)
ACTA-PORT	The Association of Cardiothoracic Anaesthetists (ACTA) perioperative risk of blood transfusion score	Age, gender, body surface area, logistic EuroSCORE, preoperative hemoglobin and creatinin, type of operation	0: 0-14 (low risk), I: 15-19(moderate risk), II: 20-24 (high risk), III: 25-30 (very high risk)
WILL-BLEED	Used to predict severe and massive perioperative bleeding in patients undergoing CABG.	Usage of Low Molecular Weight Heparin / Fondaparinux / Unfractioned Heparin, duration of pause of a potent antithrombotic drug, gender, acute coronary syndrome, anemia, eGFR, presence of critical preoperative state	I: 0-3 (low risk), II: 4-6 (moderate risk), III: >6 (high risk)
PAPWORTH	high, moderate, and low risk of postoperative bleeding	Surgical priority, type of surgery, valvular aortic disease, body mass index, age	I: 0(low risk), II: 1-2 (moderate risk), III: ≥3 (high risk)
TRACK	Transfusion Risk and Clinical Knowledge	Age, body weight, gender, complex of surgery, hematocrit level	I: <13 (low risk), II: >13 (high risk)
TRUST	Transfusion Risk Understanding Scoring Tool	Age, body weight, gender, preoperative hematocrit, preoperative Hb, preoperative creatinin, presence of previous cardiac surgery, complex surgery (Coronary revascularization + valve surgery, valve surgery, reoperations and surgery of the ascending aorta were named as complex surgery)	0: 0-1 (low risk), I: 2 (moderate risk), II: 3 (high risk), III: 4-8 (very high risk)
CRUSADE	Can Rapid Risk Stratification of Unstable Angina Patients Suppress Adverse Outcomes With Early Implementation of the ACC/AHA Guidelines	Basal hematokrit, creatinin clearance, basal heart rate, basal systolic blood pressure, gender, heart failure on admission, prior vascular disease, diabetes mellitus	0: ≤20 (very low risk), I: 21 - 30 (low risk), II: 31 - 40 (moderate risk), III: 41 to 50 (high risk) IV: ≥50 (very high risk)
ML 1 Model	Parameters used in scoring systems	Age, Gender,BMI, Operation by vessels, Cross clamb time,CPB duration, EF, Hb, Htc, Dm, HT, PAH, Cre, CRF, Anticoagulan	I: No need for ES foreseen II: The need for ES was foreseen
ML 2 Model	Combination of six scoring systems tested	Action, ACTA-PORT, WILL BLEED, PAPWORTH, TRACK, Trust, and CRUSADE scores	I: No need for ES foreseen II: The need for ES was foreseen

*Group IV doesn't exist in ACTION and CRUSADE since these don't have "very high risk" patient class. ML1 and 2: Machine learning model 1 and 2. NPV and PPV: negative and positive predicting value

ML Algorithm

In our study, a neural network was constructed through the SPSS (IBM, Chicago) program. Both dependent and independent variables were tested using the multilayer perception method in the ML algorithm. The values in the ML algorithm were selected according to logistic regression analysis and the values used in the other six scores tested. The success rate of the constructed network's correct predictions was considered as the success rate of the algorithm. The usefulness of the test was determined through AUROC analysis. Two algorithms were tested in our study. In the first algorithm (ML1), the dependent variable was erythrocyte suspension (ES) consumption, and the independent variables included patients' demographic data, laboratory data, and operational data (independent variables and factors are shown in **Table 2**). In the second algorithm, six predictive scores were combined with the ML2 algorithm as independent variables. The algorithm was trained with 290 patients (70%) and tested with 110 patients (30%). The ML algorithm consisted of a total of 14 variables and one hidden layer.

Table 2: Factors correlated with the need for ES

		ES Needed
Age	Pearson Correlation	.247**
	Sig. (2-tailed)	.000
Gender	Pearson Correlation	.466**
	Sig. (2-tailed)	.000
Body mass index	Pearson Correlation	-.077
	Sig. (2-tailed)	.121
Number of arteries operated	Pearson Correlation	.145**
	Sig. (2-tailed)	.003
Cross clamb time	Pearson Correlation	.168**
	Sig. (2-tailed)	.000
Cardiopulmonary bypass duration	Pearson Correlation	.200**
	Sig. (2-tailed)	.000
Ejection fraction	Pearson Correlation	-.172**
	Sig. (2-tailed)	.000
Preoperative hemoglobin	Pearson Correlation	-.648**
	Sig. (2-tailed)	.000
Preoperative hematocrit	Pearson Correlation	-.636**
	Sig. (2-tailed)	.000
Diabetes mellitus	Pearson Correlation	.454**
	Sig. (2-tailed)	.000
Hypertension	Pearson Correlation	.085
	Sig. (2-tailed)	.077
Pulmonary arterial hypertension	Pearson Correlation	.021
	Sig. (2-tailed)	.665
Preoperative creatinine	Pearson Correlation	.045
	Sig. (2-tailed)	.350
Chronic renal failure	Pearson Correlation	-.023
	Sig. (2-tailed)	.635
Anticoagulan use	Pearson Correlation	.100*
	Sig. (2-tailed)	.039

Correlation is significant at the 0.01 level (2-tailed).**
Correlation is significant at the 0.05 level (2-tailed).*

Transfusion Strategy

Our clinic follows a restrictive blood transfusion protocol. ES replacement is often performed when hemoglobin (Hb) levels are <7 g/dl or hematocrit (Htc) <21%. Individual planning takes tissue oxygenation into account when deciding in the range of Hb 7-8 g/dl or Hct 21-24%. Strategies to delay or avoid transfusion are preferred within the range of 8-10 g/dl. While these protocols provide a general framework, practical implementation decisions are made by the surgical and anesthesia team.

Ethical Committee

Ethical approval for this study was obtained from the Kocaeli City Hospital Clinical Research Ethics Committee (n2024-6) in 26.01.2024. Data from patients who underwent isolated CABG surgeries in the cardiac and vascular surgery operating rooms between 01.01. 2023 and 01.01.2024 were evaluated. The manuscript adheres to the applicable Enhancing the Quality and Transparency of Health Research (EQUATOR) guidelines for observational studies. In addition, the study was conducted in accordance with ethical rules including the Declaration of Helsinki.

Statistical Analysis

SPSS program was used for statistical methods, including ML algorithms. Continuous variables were expressed as mean ± standard deviation, and Student's t-test was used to compare continuous variables between patients who received transfusion and those who did not. Categorical variables were expressed as percentages and analyzed using the chi-square test. Statistical imputation was not applied to missing data. The distribution of data was assessed using Kolmogorov-Smirnov and Shapiro-Wilk normality tests, as well as histograms. ML1 and ML2 algorithms were constructed using logistic regression-based neural networks through the SPSS program. The success of the test was measured using the receiver operating characteristic curve (ROC-AUC), and the validity of logistic regression was assessed using the Hosmer-Lemeshow test. A significance level of $p<0.05$ was considered statistically significant.

RESULTS

Key parameters, including age, gender, operation type, cross-clamp time, cardiopulmonary bypass (CPB) duration, ejection fraction (EF), preoperative hemoglobin (Hb),hematocrit (Htc) levels, and anticoagulant use, were analyzed for their correlation with the need for ESTable 2 summarizes these correlations, along with other evaluated parameters such as body mass index, number of arteries operated, diabetes mellitus, hypertension, pulmonary arterial hypertension, preoperative creatinine, and chronic renal failure. There was no need for ES use in 261 patients, 73 patients consumed 1 unit, 53 patients consumed 2 units, 12 patients consumed 3 units, and 1 patient consumed 4 units.

Model 1 performance

When model 1, created with the parameters used in other scoring systems, and its performance in predicting the need for ES were examined, it reached significant predictive power for all values in the use of 0 to 3 units of ES. A visual representation of the ML model is available in **Figure 1**. When applied to the subgroup as need for >2 units of ES, it had a negative predictive value (NPV) of 67.6% and a positive predictive value (PPV) of 93.8%. Model 1 also had a NPV of 88.4% and a PPV of 75.5% regarding whether there would be any need for ES. Among all the scoring, the scoring with the highest PPV after TRUST and Will bleed scores was the ML 1 model.

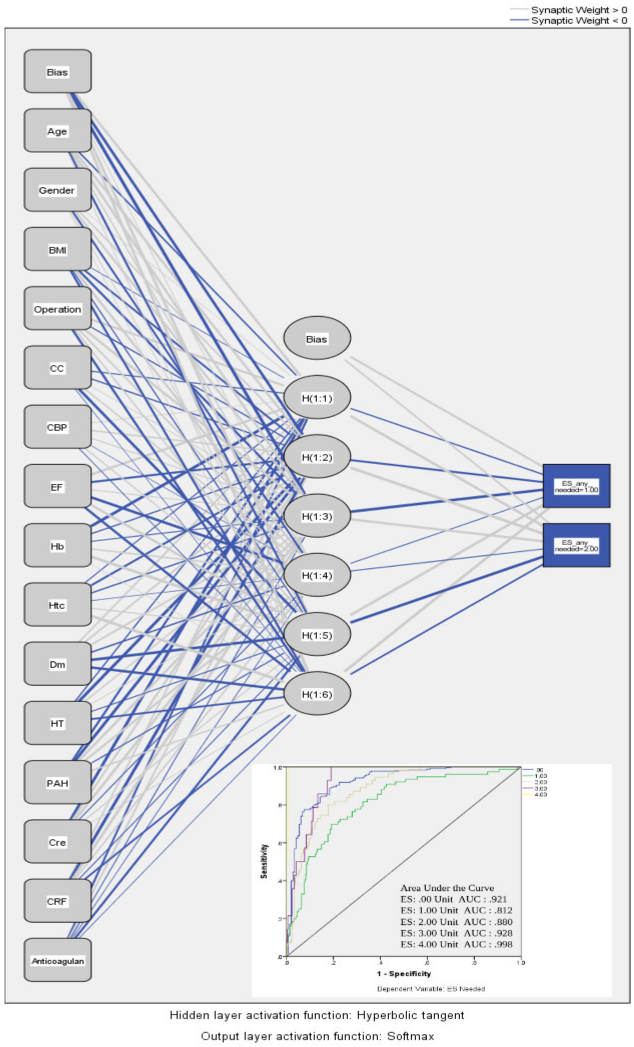

Figure 1: Schematic view and ROC analysis of ML model

Performances of traditional scoring

Table 3 presents a detailed comparison of predictive performance between traditional scoring systems and machine learning (ML) models for ES requirements. Among conventional methods, the TRUST scoring system emerged as the strongest predictor for both any ES need and >2 units of ES. The TRACK scoring system also demonstrated notable performance, achieving high negative predictive value (NPV) and positive predictive value (PPV). The ML2 model, which combined these scoring systems, showed similarly high PPV and NPV values as the standalone ML1 model, reinforcing its clinical utility. **Table 3** clearly outlines these predictive capabilities, allowing direct comparison of sensitivity, specificity, and overall accuracy across all approaches highlighting the advantages of integrated ML solutions. The ACTION score, developed for percutaneous angiographic procedures, had the lowest predictive ability among both ML models and traditional scoring.

Table 3: ES need prediction capabilities of ML models and traditional scoring

	Any ES need			>2 unit ES need		
	NPV	PPV	p	NPV	PPV	p
ACTION	93.5%	29.0%	0.048	86	31.3	0.056
CRUSCADE	74.9%	69.0%	0.044	60.9	87.5	<0.001
TRACK	84.7%	66.5%	0.043	68.6	93.8	<0.001
WILL-BLEED	76.0%	80.6%	0.040	57.5	93.8	<0.001
PAPWORTH	19.3%	85.8%	0.046	17.6	87.5	0.595
TRUST	53.8%	94.2%	0.034	37.9	100	0.002
ACTAPORT	93.8%	29.0%	0.047	87.2	56.3	<0.001
ML1	88.4	75.5	0.040	67.6	93.8	<0.001
ML 2	86.6	73.2	0.040	67.4	93.8	<0.001

ML1 and 2: Machine learning model 1 and 2. NPV and PPV: negative and positive predicting value

DISCUSSION

In this study comparing ML algorithms and known predictive scoring systems in predicting perioperative ES needs, it was demonstrated that ML algorithms have a similar decision-making ability to established scoring systems (75.5% for any ES need and vs 93.8% for predicting >2 units ES need). Moreover, the ability of these algorithms to reinforce themselves with local results and unsupervised learning suggests a potential for increasing success rates. Therefore, an ML-based perioperative bleeding prediction algorithm is a successful technique for planning blood product usage in patients undergoing CABG surgery.

Perioperative blood transfusion is an undesired treatment due to its costs and complications. Therefore, efforts are made to minimize transfusion to the minimum required units (17). CABG surgeries are among the most frequent scenarios for blood transfusion. A study about ES use in CABG patients revealed that 25% of surgical patients had 2 units of ES reserved according to hospital policy, and 20% of these units were used. The remaining blood products were returned to the blood bank (18). Effective planning within the framework of patient blood management protocols and individualized planning by surgical, and anesthesia teams appear crucial (19).

The versatility of ML algorithms and the increasing availability of health data present many potentials for more efficient utilization of limited resources in the healthcare sector. ML algorithms' potential benefits in various aspects of anesthesia have been the subject of numerous studies. The study by Hassan et al. showed that artificial intelligence algorithms could accurately predict flap necrosis in patients undergoing mastectomy (20). Another study demonstrated the benefit of ML algorithms in predicting perioperative adverse events (21-22). Among our patients, 3.7% required more ES than anticipated. Among the six existing scoring systems, only four were able to predict ES needs of 2 units or more in these patients. ACTION, ACTAPORT and PAPWORTH scores did not have sufficient predictive power. However, the, TRACK, TRUST and WILLBLEED scores had high predictive power. Both ML 1 and ML 2 scores were similar to these three scores. This observation showed that the ML model is useful in predicting both the need for any ES and the need for more than two units of ES. Having a larger sample size will always increase the predictive success of ML models. In this respect, it can be expected that the ML model will surpass the classical models in larger groups.

In a review, it was noted that 21 studies had been published on the prediction of intraoperative complications and events using ML algorithms, with the number of such studies increasing (22). A unique feature of our study is the combination of previously validated bleeding prediction scores through a single algorithm (ML2). However, this combination does not appear to be superior to individual bleeding prediction scores and ML 1 model. The selection of an algorithm for the study was not based on multiple methods, but the applicability of these algorithms was tested. Further research could explore the performance of different combinations.

Limitations of our study include the potential non-generalizability of the algorithm to other clinics and surgical teams, as well as the challenges of validating the conventional predictive scoring's consistency against different patient populations and surgical teams. However, our findings also suggest that this model can be localized and adapted to the potential and local characteristics of other clinics. Another issue is the ethical and practical implications of AI applications in decision-making and whether they can fully replace the human factor (23). These topics are still open to further investigation (24). ML predictions for ES transfusion readiness in patients prior to CABG surgery demonstrate a high degree of accuracy. It was also not inferior to other traditional classifications in predicting the need for more than two units of ES. The ML algorithm could provide a more successful preoperative planning as a local and adaptable application. These algorithms, which have potential for development in various aspects, can potentially lead to significant changes in perioperative anesthetic management and integration into hospital software when shared and adapted for use.

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