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Machine Learning in Perioperative Management: Applications and Progress

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Abstract: ***The application of machine learning (ML) technology in perioperative management is increasing, with its importance lying in enhancing surgical safety, improving patient outcomes, reducing healthcare costs, and optimizing anesthetic management. Research progress indicates that ML technology has shown great potential in perioperative risk prediction, real-time monitoring, and rationality assessment of prescriptions, and is gradually changing clinical practice in anesthesiology. We will introduce the perioperative application of ML from the aspects of preoperative assessment, intraoperative management, and postoperative recovery. In addition, we will discuss the progress and challenges of ML in recent years, as well as the future use and research directions of ML.***

Keywords: Machine Learning (ML), Perioperative, Anesthesia, Personalized Medicine.

1. Introduction

Perioperative management is dedicated to ensuring a smooth transition for patients through surgery, reducing complications, and accelerating recovery. It is a critical component in ensuring surgical success and patient health [1]. Machine Learning (ML), a branch of Artificial Intelligence (AI), is a data analysis technique that allows computer programs to automatically improve their performance through experience [2]. It focuses on developing mathematical models that can learn from data and make predictions or decisions without explicit programming. With the increase in data volume and computational power, machine ML has shown tremendous potential and application value in various fields. Perioperative monitoring and treatment involve numerous detection data and various computer control systems, making ML show great potential in the field of perioperative management [3].

2. Applications of ML in Perioperative Period

2.1 Preoperative Assessment

ML excels in preoperative diagnosis, particularly in medical image recognition, especially in early disease diagnosis and surgical planning. For instance, 3D Convolutional Neural Networks (3D-CNN) can detect pancreatic ductal adenocarcinoma in preoperative MRI with extremely high accuracy (AUROC values of 0.97 and 0.90). High-precision risk prediction models can help doctors better select surgical indications preoperatively, reduce the ineffectiveness of surgery, and improve the quality of informed consent. For example, the ML-based POTTER calculator has achieved prediction accuracy of 0.92 (internal validation) and 0.93 (external emergency surgery validation) in emergency surgery patients [4]. Preoperative optimization is a relatively new concept aimed at developing personalized optimization plans through a comprehensive assessment of patients' physical conditions. ML can rapidly assess cardiac function using 12-lead ECG, thus optimizing preoperative cardiovascular assessment [5]. Studies have established models using preoperative indicators based on ML algorithms to predict the risk of death after abdominal surgery, providing a new method for preoperative risk assessment [6]. Li et al. have developed ML applications to assist anesthesiologists in assessing specific adverse outcomes in hip repair surgery patients, such as in-hospital mortality, ICU admission requirements, and prolonged postoperative hospital stays [7]. Additionally, ML outperforms Mallampati scoring and thyromental distance in predicting difficult airways, and AI systems for predicting pediatric difficult airways have entered clinical research [8]. The application of ML in preoperative assessment is becoming increasingly widespread, playing a significant role from preoperative diagnosis to risk prediction, helping doctors make more precise clinical decisions.

2.2 Intraoperative Management

2.2.1 Application of ML in the Operation of Basic Anesthesia Skills

Endotracheal intubation, as early as 2010, Tighe of the University of Florida School of Medicine reported the use of a da Vinci robot to manipulate a flexible bronchoscope to perform endotracheal intubation on a simulated human [9]. In 2012, McGill University in Canada also successfully performed endotracheal intubation in 12 patients using the Kepler intubation system (KIS) developed by McGill University in Canada [10]. However, there are still many tasks that need to be improved for the full automation of the endotracheal intubation robot, such as the automatic cuff inflation system, the automated airway surface anesthesia system, and the automated nasotracheal intubation system.

Nerve block with the popularization of Enhanced Recovery After Surgery (ERAS), ultrasound-guided nerve blocks are widely used in anesthesia and postoperative analgesia for various surgeries [11]. Traditional ultrasound-guided nerve blocks require a high level of experience and skill of the operator, and have certain limitations in identifying complex anatomical structures and judging the position of the needle tip, which may lead to poor anesthesia effect or complications. ML provides new ideas and methods for the optimization and improvement of ultrasound-guided nerve blocks [12]. Gil applies ML algorithms to the segmentation of ultrasound neural images, in which a specific nonlinear wavelet transform is used in the feature extraction stage and Gaussian processing is used in the classification step to realize the automatic recognition of neural structures [13]. Hatt et al. trained the needle's ultrasound image splitter using a ML algorithm and used the Radon transform to find the position and orientation of the needle from the separated images, so that the position of the needle could be accurately located [14]. Therefore, the difficulties in the development of nerve blocks to automation are also being eliminated one by one.

2.2.2 Detection and Regulation of Anesthesia Depth

Current clinical anesthesia depth monitoring methods are mainly based on the analysis of brain electrical signals, with the Bispectral Index (BIS) being the most widely used [15]. Mirsadeghi found that ML algorithms can achieve more accurate results than BIS (88.4% vs. 84.2%) [16]. Shalbaf et al.'s study showed that the accuracy of ML algorithms can reach 92.91%, far higher than entropy index (77.5%) [17]. Johnson & Johnson invented the SEDASYS computer-assisted individualized sedation system. This system integrates the anesthesia discipline ASA standard monitoring items (including end-tidal CO2 monitoring) and the anesthesia automatic infusion system. After administering a loading dose of anesthetic drugs (such as propofol), the system maintains the pump at a pre-set speed and then automatically regulates the parameters of the infusion pump in real-time according to pharmacokinetic principles and anesthesia depth-related indicators [18].

2.2.3 Perioperative Complications Real-time Monitoring and Prediction.

Kendale et al. analyzed the occurrence of hypotension after induction in 13323 patients, using preoperative comorbidities, preoperative medication, induction medication, and intraoperative vital signs as clinical features. They used logistic regression, random forests, support vector machines, naive Bayes, k-nearest neighbors, linear discriminant analysis, neural networks, and gradient boosting methods for modeling and optimized the best-performing models. The results confirmed that ML algorithms can successfully predict the occurrence of hypotension after general anesthesia [19]. Hatib et al. based on the characteristics of invasive arterial pressure waves (arterial pressure wave time, wave amplitude, area under the curve, slope characteristics, Flotrac algorithm characteristics, CO-Trek characteristics, pressure reflex characteristics, etc.), judged the compensation ability of the circulatory system and created a hypotension prediction model. This model can predict the occurrence of hypotension 15 minutes before it happens [20]. Hypoxemia, like hypotension, is a common clinical event during the perioperative period and is closely related to severe complications such as myocardial infarction, acute ischemic stroke, and acute kidney injury. Lundberg et al. used hemodynamic and ventilation data obtained from monitors and anesthesia machines, as well as intraoperative medications, anesthesia interventions, and test indicators, to develop an ML-based Prescience system. The results showed that this system can double the ability of anesthesiologists to predict intraoperative hypoxemia [21]. GENG et al. used univariate analysis to identify indicators related to hypoxemia from general patient information, comorbidities, neck circumference, thyromental distance, and anesthetic medications. Then, based on these indicators, they constructed an artificial neural network model to predict hypoxemia during sedation for gastrointestinal endoscopy, with an area under the curve (AUC) of about 0.800 [22].

2.3 Postoperative Recovery Postoperative Pain Management

2.3.1 Prediction and Prevention of Postoperative Complications.

ML algorithms can predict short-term complications in patients with gastrointestinal cancer [23]. There are several Chinese doctors who integrated common clinical data and features such as body temperature, fluid intake and output, and fasting blood glucose, and used three ML algorithms: random forest (RF), support vector machine (SVM), and artificial neural network (ANN) to determine risk factors associated with complications within 7 and 30 days postoperatively. Based on these factors, researchers successfully constructed prediction models, Nomogram-A’ and Nomogram-B’, which showed good predictive accuracy with AUC values in the training and validation sets [24].

2.3.2 Pain Management

In postoperative patients, ML can analyze patients' self-reported pain scores, emotional states, quality of life and other data in real time, predict the occurrence and change of pain in time [25], and predict the required dose of analgesic drugs according to the individual characteristics of patients and postoperative pain [26]. By analyzing a patient's pain data and other relevant factors, ML can provide doctors with personalized pain management recommendations [27].

2.4 Patient Monitoring

ML technology can be used to monitor the depth of anesthesia, predict the effects of anesthetic drugs by analyzing physiological signals such as EEG, avoid intraoperative awareness or hemodynamic instability, reduce mortality and morbidity, and accelerate postoperative recovery [28]. ML technology plays a core role in the development of perioperative early warning systems. It significantly improves the quality of perioperative care and patient safety by improving the accuracy of risk prediction, achieving real-time tracking and early warning, and promoting the digital transformation of management processes [29] [30].

3. Progress and Challenges

3.1 Technological Progress

In recent years, many new ML models and algorithms have been proposed, such as Extreme Gradient Boosting (XGBoost), which outperforms traditional linear models in predictive performance for nonlinear data. Deep Neural Networks (DNN) are another type of ML model that shows potential in perioperative management. DNN processes complex data patterns by mimicking the neural network structure of the human brain and is suitable for classification and regression tasks [31]. In addition, there are Convolutional

Neural Networks (CNN) and Recurrent Neural Networks (RNN), which play roles in image analysis and biosignal processing, natural language processing, and time series data analysis [32].

3.2 Challenges in Practical Applications

Automatically acquired data has issues such as instrument interference, erroneous data generation, and non-uniform standards between instruments from different manufacturers. Perioperative big data has characteristics such as cross-granularity, high-dimensional multimodality, mixed noise, and heterogeneity in ontological scales, leading to low accuracy and poor generalization in risk warning and decision support models built based on conventional scale ML [33]. The ethical and legal consequences of AI algorithm-baseddecision-making are of concern and require appropriate regulation. The underrepresentation of certain populations in datasets used for AI model training can lead to inherent biases, affecting medical services and patient outcomes [16].

4. Future Directions

4.1 The Importance of Interdisciplinary Collaboration

Interdisciplinary Collaboration Integrating diverse expertise from physicians, researchers, technology experts, and policymakers is crucial for effectively addressing the ethical and regulatory challenges related to the implementation of AI algorithms [34]. The success of ML requires interdisciplinary collaboration, which not only improves the quality of patient care but also promotes the development and innovation of AI technology while ensuring the alignment of ethics and responsibility [35].

4.2 Integration of ML Into Clinical Practice

To facilitate the broader application of ML algorithms in clinical practice, it is necessary to enhance the quality standards, transparency, and interpretability of models [36]. Chadia et al. emphasized the importance of interdisciplinary collaboration and proposed the concept of Hybrid Intelligence (HI), which combines human intelligence with artificial intelligence. This collaboration can overcome the limitations of AI and improve the accuracy of predictions through the cooperation of humans and algorithms. Current clinical decision support tools (Built-in ML algorithms) show significant potential based on the chosen algorithm, including disease classification, risk stratification, dosage recommendation, pattern recognition, precision treatment, and health monitoring. To benefit from AI advancements, physicians need direct control over ML system suggestions, a solid understanding, and the ability to interact easily with decision support tools, interpreting the results generated by ML algorithms [37].

4.3 Long-term Vision of Artificial Intelligence in Perioperative Management

The long-term vision of AI in perioperative management is to achieve more precise diagnostics, improve surgical quality, optimize clinical decision-making, expand perioperative care, and ensure the security and privacy of patient data.

5. Conclusion

Currently, ML has been successfully integrated with clinical practice, with ML assistance enabling precise perioperative management, reducing anesthesia risks, and postoperative complications. Additionally, ML-assisted wearable cardiac ultrasound monitoring devices have achieved real-time monitoring of cardiac function during surgery, providing scientific evidence for anesthesiologists and ensuring the stability of patients' vital signs during the surgical process. ML algorithms can also filter large amounts of data, detect patterns and similarities, and learn from past analyses of similar cohorts to provide decision support. These technologies not only enhance the precision and safety of intraoperative monitoring but also help anesthesiologists optimize decisions, reduce intraoperative risks, and significantly improve patient safety and surgical success rates. The application of ML in perioperative management is expected to significantly change practice, including preoperative assessment and accurate risk prediction, intraoperative management, and postoperative complication management. ML can analyze surgical videos, learning curves, and near-misses, reducing errors in minimally invasive surgery. Furthermore, ML has also shown effectiveness in reducing postoperative surgical site infections and identifying anastomotic leaks in electronic health records. With technological advancements and increasing data, the predictive power of ML models will be further improved, providing more precise decision support for the enhancement of perioperative medical quality.

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