EDITORIAL VIEW **PERIOPERATIVE USE OF AI**

Exploring new horizons in intraoperative hemodynamic management using artificial intelligence

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ABSTRACT

Artificial intelligence (AI) has revolutionized every field of human life. It has a more pronounced effect in the monitoring and surveillance, and healthcare professionals have been quick to recognize its ability to show and perform in a fraction of a second, what took hours, if not days, to accomplish. More and more complex medical gadgets have been developed, which are super-fast. This editorial highlights the use AI to identify and deduce inferences from the heart rate variability (HRV) in the operating room. HRV is a pivotal factor for anesthetists, reflecting intraoperative stress, brainstem activity, and the state of the autonomic nervous system (ANS) as well as cardiac health. Various AI algorithms have been developed for monitoring HRV, including pulse-beat-based algorithms. The readers are urged to learn the use of AI to manage the sick to the benefit of the patient.

Abbreviations: AI: artificial intelligence, ANS: autonomic nervous system, DNN: deep neural network, HCM: Hypertrophic cardiomyopathy, HRV: heart rate variability, PPG: photoplethysmography, RRI: R-R intervals

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INTRODUCTION

Hemodynamic monitoring and artificial intelligence are expected to become prevalent in all aspects of the perioperative period and closely integrated within the field of anesthesiology in the near future.[1] Future developments in AI-based systems will not surpass the anesthesiologists; instead, they will enable them to concentrate on more complex responsibilities. AI merely transforms its function. While machines can assess risk quantitatively, they are incapable of making valuable decisions, as they do not possess the nuanced understanding inherent to the practice of medicine. One of the primary challenges faced by anesthesiologists is the management of the four essential vital signs: heart rate (HR), respiratory rate (RR), blood pressure (BP), and oxygen saturation (SpO_2) within the operating rooms. The morphology of the electrocardiogram (ECG) is of significant importance in an operating room setting.

In this issue, we present innovative artificial intelligence algorithms designed for the management of vital signs, which represent the four most significant aspects of hemodynamic monitoring for anesthesiologists, alongside algorithms for efficient interpretation of ECG features.

Heart rate variability (HRV) in the operating room is a pivotal factor for anesthetists, reflecting intraoperative stress, brainstem activity, and the state of the autonomic nervous system (ANS) alongside cardiac health. Various AI algorithms have been developed for monitoring HRV, including pulse-beat-based algorithms, high-performance R-peak detectors, heartbeat classifiers that compare and merge, predictive autocorrelation, nonlinear predictive interpolation, detrending using smoothness prior, wavelet-based trend removal through nonlinear filtering, and autoregressive (AR) model-based techniques that emphasize R-R intervals (RRI). In these methods, correction of RRIs is employed to fulfil specific consistency criteria, traditionally involving deletion and interpolation. However, these methods possess numerous shortcomings. Examples of these flaws include the distortion of HRV parameters or inaccuracies in HRV parameter computation due to electrocardiographic morphological artefacts. New models, such as a novel AI-based HRV analysis algorithm (NAIHA), analyze the ECG morphology alongside the sequence of beats using a two-stage deep learning (DL) classifier. This approach subsequently searches over successive time intervals to identify eligible windows before computing the HRV parameters on the RRI series, excluding abnormal RRIs, thereby alleviating the burden on clinicians without compromising the accuracy of HRV analysis, potentially leading to wider adoption.[2] These algorithms can enhance our understanding of cardiac function and the autonomic nervous system, helping to prevent unexpected events like myocardial infarction, which can lead to poor outcomes during surgery.

The ECG provides a wealth of physiological information that is distinctive and indicative of various health conditions, such as hypertrophic cardiomyopathy, arrhythmia syndromes, silent atrial fibrillation, and valvular heart diseases. Integrating AI with a standard ECG offers a widely accessible and cost-effective diagnostic tool that does not require body fluids or reagents. This advancement has significantly enhanced clinicians' diagnostic capabilities, transforming the ECG into a potent screening instrument that can also facilitate monitoring and evaluating therapeutic responses. Hypertrophic cardiomyopathy (HCM) can lead to symptoms or even sudden cardiac death in younger individuals. Although several ECG criteria have been suggested for its diagnosis, none have demonstrated consistent effectiveness.[2]

Previous efforts to identify HCM through AI have concentrated on characteristics of high-risk patients and specific ECG criteria.[3] It is important to note that approximately 10% of HCM patients may present with a 'normal' ECG, which renders traditional diagnostic criteria and algorithms ineffective. This suggests that the AI ECG algorithm does not rely solely on the conventional ECG features typically associated with HCM for its diagnostic capabilities. The judicious use of AI could offer reassurance to patients and mitigate the need for unnecessary and costly diagnostic procedures linked to manual interpretations, thereby enhancing the efficiency of healthcare resource utilization.

Arrhythmia syndromes, like long QT syndrome (LQTS), demonstrate incomplete penetrance, indicating that the manifestation and severity of the disease can vary significantly among individuals, even within the same family. Given that diagnosis primarily relies on ECG findings, there is a considerable risk of human error in interpretation. Consequently, AI presents an opportunity for more accurate assessment of diagnostic indicators and the capacity to identify diagnoses in cases of incomplete penetrance. This capability may stem from the capability of neural networks in recognizing subtle morphological changes in ECG readings. A prime example of this is the measurement of the QT interval. A deep neural network (DNN) was trained using ECG data from 250,767 patients, subsequently tested on an additional 107,920 patients, and validated with a further 179,513 patients, utilizing the institutional ECG repository where the cardiologist's over-read QTc served as the gold standard. The DNN utilized a two-lead ECG input. Strong agreement was observed in the test set between the DNN predicted values and the gold standard. Moreover, when assessed in a prospective genetic heart disease clinic population, including LQTS patients, the DNN maintained robust performance. For a QTc cut-off of >500ms, which serves as a significant diagnostic and risk marker for LQTS, the sensitivity and specificity were recorded at 80.0% and 94.4%, respectively, highlighting its strong potential as a screening tool.

Notably, even in cases where the QTc appears normal, concealed LQTS has been identified through computerized analysis of T-wave morphology. The DNN was applied to the complete ECG data from all patients in the genetic heart disease clinic (N=2059) diagnosed with LQTS, as well as those who were evaluated and subsequently discharged without a diagnosis. The QTc interval alone successfully identified patients with LQTS who had a QTc <450ms in comparison to those without LQTS. This suggests AI's potential as a guiding tool for clinical evaluation.[3]

Machine learning (ML) is a branch of AI that relies on algorithms to identify hidden patterns from datasets. Various algorithms are employed to assess and forecast blood pressure (BP) along with other indicators of cardiovascular risk. Elevated BP is recognized as a significant contributor to cardiovascular diseases (CVD). Since 1999, numerous efforts have been made to utilize neural networks for the analysis of BP. One particular study aimed at estimating CVD risk by incorporating factors such as age, gender, race, body mass index (BMI), waist-to-height ratio, and both systolic and diastolic blood pressures as input variables, while biochemical markers (including HDL, LDL, total cholesterol, fibrinogen, and uric acid) served as output variables in an Artificial Neural Network (ANN) analysis, achieving an accuracy rate of 82.6%. Another investigation involving 73 participants collected 14 attributes from ECG and photoplethysmograms. By applying a genetic algorithm, relevant blood indicators were identified for each individual. A continuous BP estimation model was subsequently developed using multivariate regression, demonstrating a strong correlation with actual BP measurements (correlation coefficients of 0.852 for systolic blood pressure and 0.790 for diastolic blood pressure), thereby reinforcing the notion that AI can effectively utilize non-invasive biophysical parameters to estimate blood pressure with considerable accuracy.[4]

Respiratory rate (RR) serves as a crucial physiological parameter and is one of the four essential vital signs utilized for identifying medical conditions. Recent advancements in techniques for estimating RR have emerged. Over the last few decades, pulse oximetry has been recognized as a vital tool for assessing the percentage of oxygenated blood, known as SpO_2, carried by hemoglobin. This non-invasive procedure is painless and evaluates the effectiveness of oxygen transport from the heart to various body regions. Various AI-based methods have emerged for extracting significant features from photoplethysmography (PPG). Recent research has advocated for the use of PPG in assessing both RR and SpO_2. This innovative approach employs ML models that leverage features from PPG signals. New strategies have been developed, incorporating advanced time-domain RR estimation and modulation fusion techniques. For instance, an algorithm has been designed to automatically remove PPG segments affected by movement artifacts, enhancing its applicability for measuring RR in pediatric patients within emergency department settings.[5]

Continuous monitoring of SpO_2 levels is essential for patients with cardiac and pulmonary disorders undergoing surgery. There are two primary types of pulse oximeters: Transmittance and Reflectance. Transmittance pulse oximeters are commonly utilized in clinical settings due to their high accuracy and stability; however, they are restricted to measuring SpO_2 from peripheral sites only. In contrast, Reflectance pulse oximeters can be employed at multiple sites, including the finger, wrist, chest, and forehead, and are less susceptible to erroneous readings caused by vasoconstriction and variations in perfusion. Transmittance pulse oximeters calculate SpO_2 by utilizing the R-value, which is derived from the ratio of the alternating current (AC) to direct current (DC) components associated with red and infrared (IR) light.[3] A similar methodology has been suggested for SpO_2 calculation in reflectance pulse oximeters. This approach involves deriving SpO_2 values through a calibration curve established using reference SpO_2 values obtained from transmittance photoplethysmography (PPG) signals, alongside the R-value computed from reflectance PPG signals.[4] Despite their potential, reflectance pulse oximeters have not gained widespread acceptance in clinical practice due to issues with inaccurate measurements and unreliable R-value-based calibration techniques.

The determination of SpO_2 from R-value alone can be misleading, particularly in the absence of arterial pulsations, which can lead to an inflated R-value. Additionally, the R-value is influenced by various lighting and environmental conditions. Consequently, there is a pressing need for the development of innovative techniques for calibration-free SpO_2 computation using reflectance methods. Researchers are currently exploring ML models for SpO_2 estimation utilizing reflectance PPG signals obtained from the finger via a specialized data acquisition platform.[5] The model underwent evaluation utilizing clinical data gathered from 95 individuals, whose SpO_2 levels ranged from 81% to 100%. This was achieved through a specialized SpO_2 data acquisition platform, complemented by reference measurements. The developed model demonstrates an absolute mean error of 0.5% and an accuracy of 96±2% within the error band for SpO_2 values between 81% and 100%.

Conflict of interests

The authors declare that there was no conflict of interest involve.

Authors contribution

SS: Conceptualization, Manuscript editing
KL: MN: Manuscript writing and editing
Both authors have approved the manuscript.

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