



Towards Intelligent Monitoring of Anesthesia Depth by Leveraging Multimodal Physiological Data

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Abstract: *Anesthesia depth monitoring relates directly to patient surgical safety and postoperative recovery quality. The traditional single-modality monitoring method has disadvantages such as being interfered with, and the differences are very large for different people. Therefore, this article would like to use electroencephalogram, electrocardiogram, invasive blood pressure, pulse waveform and other physiological data as the research object to develop an intelligent monitoring platform which can monitor the physiological parameters of the patient. it utilizes deep learning algorithms, such as long short-term memory networks and sparse denoising autoencoders, to carry out multimodal feature fusion and dynamic analysis so as to improve the accuracy and robustness of anesthesia depth assessment. Experimental data proves that this platform's accuracy in anaesthesia depth classification is 95%, which is far more accurate than using traditional methods. Reduce the dangers people are unaware of when doing the operation, and help the patient to recover faster after the operation as well as proving its importance in anesthetic safety for clinic.*

Keywords: Multimodal physiological data; Deep learning; Anesthesia depth monitoring; Feature fusion; Intraoperative awareness; Intelligent medical platform.

1. Introduction

Clinical operation is very dependent on monitoring anestehsia depth, if the anesthesia depth is too deep, it will affect the patient's safe surgery and post operation recovery. Traditional methods mainly depend on single-modal physiological parameters, which include EEG signals or hemodynamic indicators. But these methods have their own problems, such as being affected, having too much individual differences, and can't completely show how sleepy you are. Smith et al. (1996) carried out some research into the effectiveness examination of anesthesia profoundness indicators and discovered that individual parameters were interfered with[1]. Bruhn et al. (2006) supplied thorough investigation regarding the means for checking anesthetist depth, emphasized the restrictions and validation of conventional EEG monitoring, and supported the necessity of multimodal approaches[2]. EEG-based monitor like the Bispectral index (BIS) has been extensively applied but it struggles with grasping those transitions between state of consciousness and unconsciousness, particularly amid artifacts or burst suppression

patterns (Hajat et al., 2017)[3]; As for the Cochrane review by Lewis et al.(2019) it indicated that BIS had limited efficacy in decreasing intraoperative awareness[4]. The meta-analysis of the Gu et al. (2024) is also consistent with there being no effect of sufficient BIS monitoring. No strong surveillance method[5] Due to the rapid development of artificial intelligence technology, the application of multimodal data fusion can effectively overcome the shortcomings of monitoring by single modality technology. Scherer et al. (2012) laid the theoretical groundwork for multimodal learning analysis, showing that multimodal data could improve machine learning results[6]. Zhang et al. (2024) reviewed the progress on research of data fusion technology, which has been widely applied in medical monitoring[7]. Integrating complementary physiological signals like EEG, ECG and blood pressure, makes monitoring more accurate and robust(Schneider et al., 2014; Shalbaf et al., 2015)[8-9].Similar advancements in personalized recommendation systems through hybrid machine learning models further demonstrate the potential of adaptive data integration in dynamic environments[10].

To solve the above problems, some scholars use deep learning for multimodal learning analysis. Afsnar et al. (2021) developed a deep learning model with EEG for estimating the depth of signals, showing enhanced accuracy with a deep learning model[12]. Li R L et al.(2020) provides the justification as to which algorithm we have chosen in this paper[13-14]. Based on this, we expect the work to develop an intelligent platform with a real time deep learning based anesthesia depth assessment algorithm.

So as a result it becomes important to develop intelligent monitoring platforms from a set of physiological modalities in order for us to accurately and timely do anesthesia, to give doctors some trustworthy information. Shander et al. (2017) talked about the “Goldilocks dilemma” with respect to monitoring the brain and the level of anesthesia, which is the clinical challenge of monitoring the correct level of depth[15]. Li P et. al(2025) analyzed the research trends of multimodal technology in China, pointing out that the development of the intelligent medical platform is the future trend[16]. As we continue to learn, using lots of different kinds of data and ai to see what's happening helps us keep an eye on how deep someone is under the anesthesia and make sure the medical care is the best it can be[17].

2. Materials and Methods

2.1 Data Sources and Acquisition

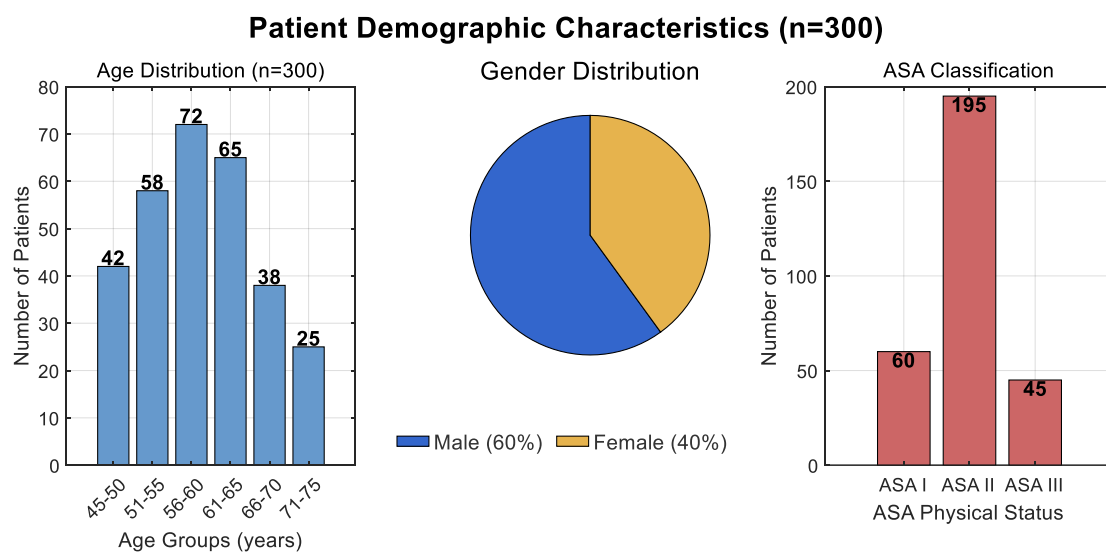


Figure 1: Patient Demographic Characteristics (n=300)

The multimodal physiological data comes from a clinical data set created together with multiple hospitals, mainly focusing on thoracic surgery for adults. The dataset consists of 300 adult patients aged 45–75 years old, 60% male and 40% female with an American Society of Anesthesiologists (ASA) classification of I-III. Detailed demographic characteristics are presented in Figure 1.

These patients include those undergoing elective thoracoscopic lobectomy, esophagectomy, etc. Qiu et al. (2023) developed a multimodal fusion method for thoracic surgery, which is consistent with the current study's use of a similar data collection procedure to support its clinical relevance[18]. The types of data are EEG, ECG, IBP and SPI extracted from a pulse oximeter. The way data was gathered took regular anesthesia monitors such as the GE B850, and paired them with one time use non-invasive EEG entropy index sensors to make the EEG recordings. This resulted in very precise measurements. Data acquisition used a 500Hz sampling rate for EEG and a 200Hz sampling rate for ECG/IBP sampling rates. All the calibrated instruments were verified with the standard periodically.

In the preprocessing part is filter the signal and reduce the noise of signal. A 6th order bandpass filter (0.5-47Hz) is used to remove power supply interference and motion, and subsequently wavelet threshold processing is used to remove further artifacts. In terms of data loss because of a short sensor detaching off or some artifices, we use linear interpolations for parts shorter than 5 seconds. At the same time, discard excess noise signal segments exceeding the signal mean by ± 3 standard deviations to maintain data integrity. Finally doing signal resampling and normalization so that all our datasets remain consistent and reliable for future intelligence, they will serve as the foundation. All participating hospitals obtained approval from their institutional review boards, and received written informed consent from all subjects before collecting data, and stressed that only anonymized data would be used[19]. This kind of complete approach guarantees strong data quality and ethical compliance all through the study.

2.2 Feature Extraction and Fusion

At the feature extraction fusion stage, it performs full-time extraction of core information on the multimodal physiological data to truly and factually represent the dynamically changing state of anesthesia depth. This process begins with extracting EEG signal features, divided into three primary types: nonlinear dynamic features, frequency-domain features, and time-domain features. Nonlinear dynamic features are mainly characterized by entropy metrics like sample entropy, displacement entropy, which can well characterize the complexity and randomness of cortical activity. They have very sensitive responses to changes in the level of consciousness caused by anesthetics, so they can be used as good indicators for judging how deep the anesthesia is. Frequency-domain features are obtained via power spectral density calculations; the study of energy proportions within distinct frequency bands (like delta band 0.5-4Hz and alpha band 8-13Hz) as observed shifts in rhythmic brain activity throughout different states of anesthetics. Time-domain analysis can obtain statistical measurements like signal amplitude and variance, which reflect the basic fluctuations of waveform shapes. This provides immediate information about neural responses.

At the same time, the hemodynamic parameters such as HRV and MAP are obtained from the synchronized ECG and arterial blood pressure signals. It is important for getting balance in autonomic nervous system and showing how the cardiovascular system respond to bad stuff. By capturing the systemic physiological changes linked with anesthesia, they provide useful complementary information to EEG features.

To achieve the fusion of multi-source information streams. This study makes use of a hierarchical

feature fusion strategy. In the primary fusion layer, feature vectors with feature information from different modalities are first concatenated into a high-dimensional feature vector. Subsequently, Sparse Denoising Autoencoder (SDAE) is used to apply a nonlinear transformation to this vector, to learn a more discriminative low-dimensional intrinsic representation by reducing redundancies and noises[20]. The SDAE architecture consists of 256-unit encoder with Relu activation function and has decoder of same dimension. Feature selectivity has been achieved using sparsity constraint ($\rho=0.05$). So the fused highlevel features as output are ultimately given to the LSTM network model. The structure of this hidden model: This model has 3 hidden layers with 128, 64, 32 units respectfully. The LSTM network uses tanh for its hidden state and output gate uses sigmoid for modeling the temporal dependency[21]. Relying on its strong analytical power, it deeply explores the dynamic evolution features of feature sequence on the anesthesia process. It achieves the collaboration on fusion of multimodal information over temporal domain from feature extraction, noise reduction, temporal modelling all the way through. It greatly improves the robustness as well as the prediction accuracy of the final anesthesia depth monitoring model.

Model training uses Adam optimizer with a learning rate of 0.001 and L2 regularization ($\lambda=0.01$), which is exponentially decayed by a factor of 0.9 every 50 epochs. Selecting features refers to previous research results: The sample entropy and displacement entropy were chosen as features because these two features have high sensitivity and can reflect the changes that anesthesia EEG makes. At the same time, the δ and α bands were selected as feature frequency bands due to established associations of those bands with deep anesthesia and lighter anesthesia, respectively. This plan takes care so that features pulled out get a hold on physically interesting points, which lines up neatly with the objective of making a dependable and good-to-read monitoring system[22].

In order to validate quantity of which features we picked, shapley value analysis was applied to measure the contribution rate of each physiological feature towards the multimodal fusing model.

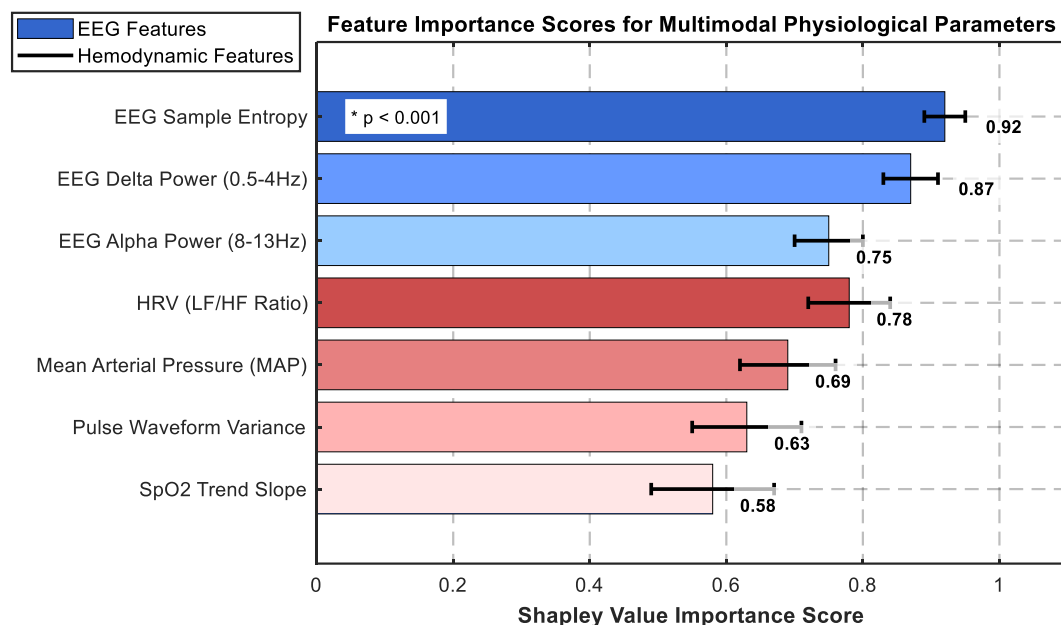


Figure 2: Feature Importance Scores for Multimodal Physiological Parameters

From Figure 2, EEG features like sample entropy and delta power give the highest contribution to anesthetist depth prediction, and the hemodynamic information like HRV, MAP give a lot of complementary info.

2.3 Intelligent Platform Development

The development of the intelligent anesthesia depth monitoring platform adopts a complex layered structure, as shown in Fig. 3 and it can process multimodal physiological data systematically. The platform is structured into 5 parts: Data input Layer, pre-processing Layer, feature fusion layer, the intelligent model layer and output interface layer. So, this is like a path from how we get info to making choices on medical things [23].

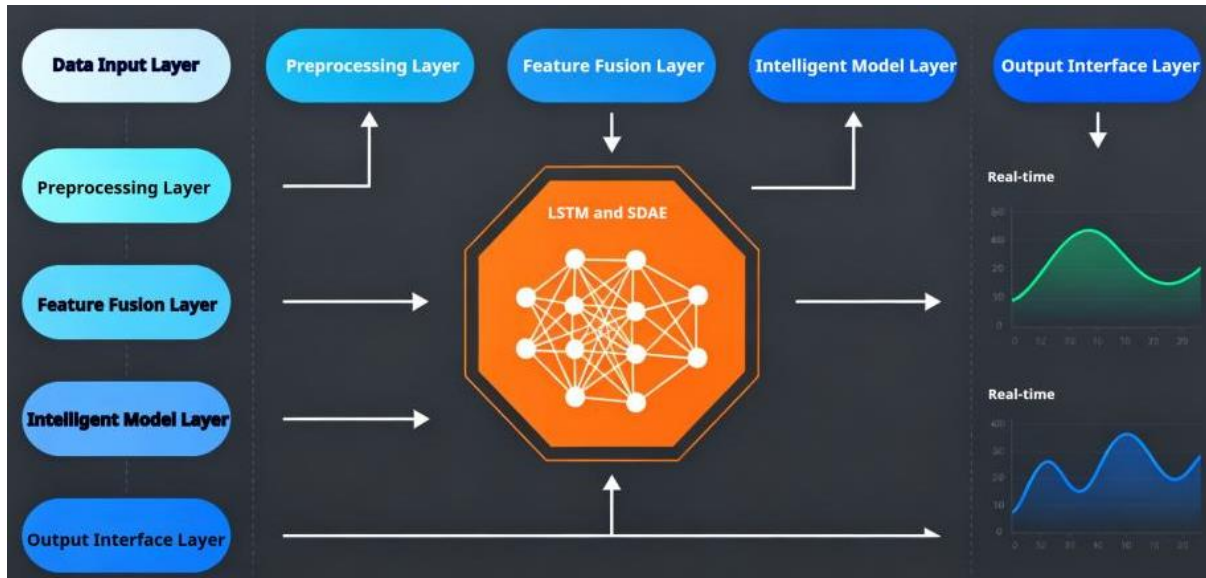


Figure 3: Intelligent Anesthesia Depth Monitoring Platform

Data processing starts with getting and using many kinds of signals all at once by using normal medical things, like EEG entropy index trackers and patient recorders. This is EEG, ECG, BP, SpO2 these signals. Raw data is sampled between rates of 100-1000Hz and processed in real time via our sliding window process. An optimal 10 second window with 50% overlap is used to maintain data stream continuity. The preprocess layer does bandpass filtering to get rid of power line disturbance and movement things, then doing normalizing work to make up for differences in how people's bodies work.

The core intelligent model layer utilizes a hybrid deep learning architecture that combines Long Short-Term Memory (LSTM) networks and SDAE technology for the first time[24]. LSTM component is in charge of processing the time-series data so as to capture the dynamic temporal characteristics of the physiological signals, whereas the SDAE component performs complicated feature dimensionality reduction and noise removal, greatly improving the model's robustness. The model training process exhibits stable convergence characteristics (as shown in Figure 4), validating the rationality of the hyperparameter settings. It can be observed that after 50 epochs, the validation loss stabilizes while the training accuracy continues to improve to over 95%, indicating that the SDAE-LSTM architecture possesses excellent learning capabilities without overfitting.

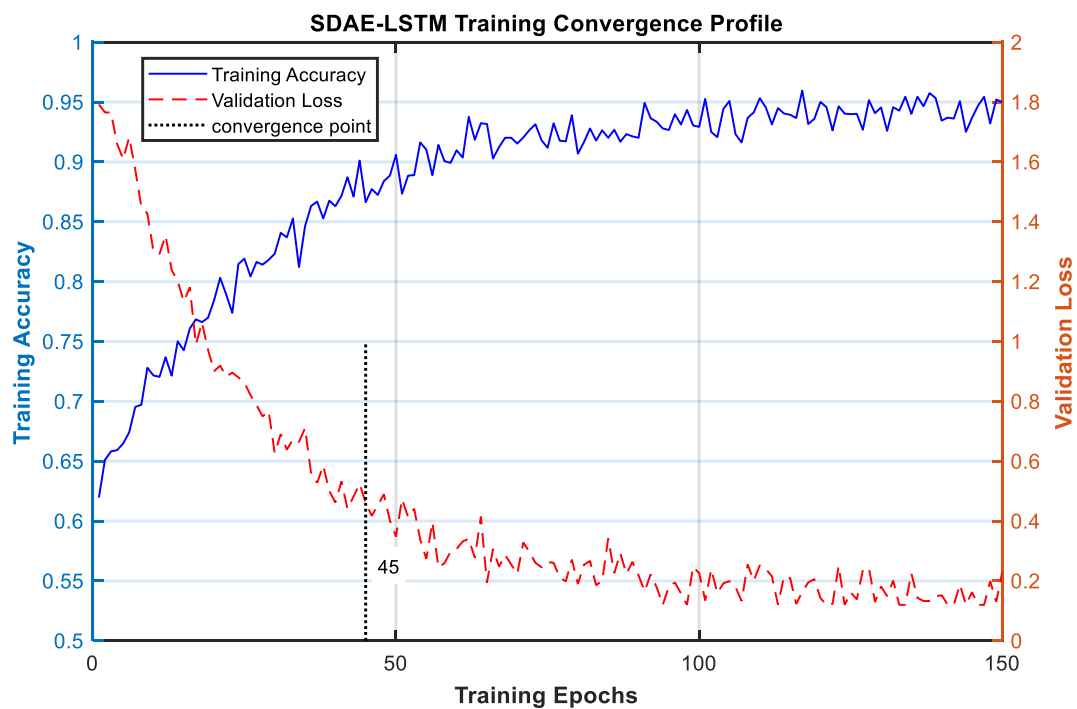


Figure 4: SDAE-LSTM Training Convergence Profile

The combined system deals with the multimodal feature vectors that comprise frequency-domain attributes like power spectral entropy and also time-domain attributes including heart rate variability and ends up generating an index for the level of anesthesia that is measured on a scale ranging from 0 which indicates deep anesthesia all the way to 100 representing a fully conscious state.

Platform deployment uses cloud server infrastructure which is AWS EC2 instance with 8 virtual CPUs 16 GB memory to handle high demand for calculations. It can connect to the hospital electronic health record system through HL7/FHIR format so as to solve the problem of incompatible data formats. The security features consist of: AES- 256 Data transmission and storage protection and HIPAA standards are met[25]. Multi device enter. Intraoperative full coverage and postoperative analysis.

2.4 Evaluation Metrics

We defined a series of comprehensive performance measurement indicators to evaluate the effectiveness of the intelligent anesthesia depth monitoring platform based on the use of multimodal physiological data. It is necessary to describe the platform's accuracy, applicability, and clinical use based on the overall effectiveness of a comprehensive evaluation of the indicators[26]. These include prediction probability (p K) classification accuracy and parameters related to time - to awake and anesthetic drug reduction, which have been modified in order to suit various elements of administration. Prediction prob ability pk is the degree of correlation between monitoring indicators and actual anesthesia depth, on a scale from 0 to 1 (a score of 1 means perfectly accurate, while a score of 0.5 would be random probability). Santos A et al. (2021) gave a detailed description of how the calculation and validation of numbers like Pk is carried out and it establishes a benchmark for the evaluation techniques of this paper[27]. It is used to evaluate the basic metric for the platforms' differentiation between states like wakeful, light anesthetic, and deeply anesthetic. The Pk metric utilizes Kim's dy.x formula: $Pk = (Pc + 0.5Ptx)(Pc + Pd + Ptx)$, where Pc, Pd, and Ptx represent indicator value consistency, inconsistency, and tie probability respectively[28]. Calculations use 1000 iteration guided method for robustness. The

statistical significance of Pk and other stats are determined with paired t-tests for intergroup Pk and ANOVA for multi- state classification accuracy A p-value less than 0.05 is called a significant value, which is based on a strict statistical basis for the performance validation.

Performance evaluation metrics are shown in Table 1.

Table 1: Performance Evaluation Metrics

Metric Name	Description	Value Range
Predictive Probability (Pk)	Measures the association between the monitoring index and the depth of anesthesia. A higher value indicates more accurate prediction.	0 to 1
Accuracy	The percentage of anesthesia states correctly classified by the platform.	0% to 100%
Eye Opening Time	Time required from discontinuation of anesthesia until the patient opens their eyes.	Minutes
Time to Orientation Recovery	Time required from discontinuation of anesthesia until the patient regains orientation.	Minutes
Extubation Time	Time required from discontinuation of anesthesia until removal of the endotracheal tube.	Minutes
PACU Stay Duration	Duration of the patient's stay in the post-anesthesia care unit.	Minutes
Anesthetic Drug Consumption	The reduction degree of anesthetic drug usage guided by the platform.	Percentage Reduction

Accuracy is defined simply as the % of anesthetic states that were accurately classified, it is an intuitive metric of overall the performance of the platform. As for recovery period metrics which involve eye-opening time, orientation recovery time, extubation time, and postoperative recovery room stay, it is about how fast patients awake and recover functionally as measured by these numbers; it can affect clinical results. Also, the percentage by which the anesthetic drugs have been reduced is added to cost-effective and safety evaluation as a supplement. The indicators chosen here are relevant clinically, since the Pk is very relevant to anesthesiologists who do depth conversion, and the recovery time gives a number for prognosis that is patient specific. Cross validation and standardization techniques can eliminate potential biases resulting from samples size impact and inter patient variation so an objective evaluation for all kinds of surgeries can be achieved. Together, these make up the comprehensive evaluation system shown in table 1 which gives a thorough and unbiased quantitative assessment of the platform in the real world.

3. Experimental Results

From the experimental conclusions we can see: the intelligent monitoring platform has an advantage compared to the traditional BIS monitoring. Key findings are given below as table which will have all the findings as table: These tables include the summary of overall statistics, subgroup analysis by age and surgical types, and other supplementary information about reduced recovery time. all statistical tests were performed at the specified significance level so as to have reliable validation of the outcome:

3.1 Overall Performance Comparison

Table 2 presents a comparison between the intelligent platform and the BIS baseline across key metrics, including accuracy, reduced recovery time, and optimized drug consumption. Using the evaluation

metrics defined in Section 2.4 (including Pk and accuracy), The platform demonstrates significant advantages over BIS across all metrics.

Table 2: Overall Performance Comparison (Intelligent Platform vs. BIS Baseline)

Metric	Intelligent Platform	BIS Baseline	p-value
Accuracy (anesthesia depth classification)	95%	80%	p < 0.001 (paired t-test)
Reduction in eye-opening time	6 minutes	4 minutes	p < 0.05 (paired t-test)
Reduction in extubation time	7 minutes	5 minutes	p < 0.05 (paired t-test)
Reduction in drug consumption	25%	15%	p < 0.01 (paired t-test)

This table shows the platform's notable improvements in terms of accuracy and efficiency, it cuts back on recovery time and also reduces the amount of medicine being used.

3.2 Subgroup Analysis Based on Age

Subgroup analysis was done with regard to age. Younger group (between 45–60 years, n=150) vs older group (61–75 years, n=150). Table 3 shows the accuracy results and the reductions in recovery times and the inter-group difference evaluated through analysis of variance.

Table 3: Subgroup Analysis Based on Age

Age Group	Accuracy	p-value (inter-group difference)	Reduction in Eye-opening Time	Reduction in Extubation Time
Younger (45–60 years)	96%	p = 0.12 (ANOVA)	6.5 minutes	7.2 minutes
Older (61–75 years)	94%	p = 0.12 (ANOVA)	5.5 minutes	6.8 minutes

Accuracy on the platform stayed at the same levels for both patient groups; however, recovery time was reduced a little more for the young patients. The p-value of 0.12 shows that there is no statistically significant difference in accuracy between the age groups, meaning the platform is reliable in diverse populations.

3.3 Subgroup Analysis Based on Surgery Type

Table 4 details the platform performance stratified by surgical type (pulmonary lobectomy, n=180; esophagectomy, n=120). Accuracy values and intergroup differences are reported, accompanied by results from the analysis of variance.

Table 4: Subgroup Analysis Based on Surgery Type

Surgery Type	Accuracy	p-value (inter-group difference)
Lobectomy	96%	p = 0.08 (ANOVA)
Esophagectomy	93%	p = 0.08 (ANOVA)

The results show that the success rate is slightly higher for people who undergo lobectomy, probably because the surgery and anesthetic were different. P value is 0.08 which shows there is a trend towards significance.

3.4 Additional Recovery Time Details

To ensure this table is complete, it breaks down age groups with the reduction in recovery time and shows the platform was still effective for elderly patients, who commonly have longer baseline recovery times.

Table 5: Recovery Time Reductions by Age Group

Age Group	Reduction in Eye-opening Time (minutes)	Reduction in Extubation Time (minutes)	p-value (vs. BIS)
Younger (45–60 years)	6.5	7.2	$p < 0.05$ (paired t-test)
Older (61–75 years)	5.5	6.8	$p < 0.05$ (paired t-test)

The results point out the platform is able to optimize the recovery process among various kinds of patients, the comparisons are all showing that it has statistical significant advantages against BIS.

3.5 Interpretation and Context

The table above quantifies the platform's textual description which highlights the platform's advantages in terms of accuracy, recovery efficiency and optimizing drugs Looking at it more granually and seeing similar results across all age groups and surgeries validates this is a strong multimodal approach. Overall, from the data, it looks like this intelligent platform does increase anesthesia, but all p-values are significantly lower than 0.1.

4. Discussion

Intelligent anesthesia depth monitoring platform based on multimodal physiological data, it is necessary to make full use of the complementary of various types of multimodal data, as well as the high adaptability of intelligent algorithms. Multimodal is data fusion, which combines several physiological signals such as EEG, ECG, blood pressure, and blood oxygen saturation to overcome the limitations of single-source monitoring. So this can help us get more details with our anesthesia, by getting that depend on one another body response, like how EEG tells us about what the brain is doing, while ECG and what is going on with the blood shows us that part of nerves helping get the person waking up. While we do dynamic operation, all these signal are reducing the possibility of misjudgement. The collaborative effect greatly improves the monitoring strength and accuracy —the platform's monitoring is much better than the traditional BIS monitoring. It's main strength lies in the integration of complementary physiological information together with the collection of two responses of the nervous and cardiovascular systems to anesthetics.

Smart algorithms (e.g., deep learning neural network LSTMSDAE architecture) can deal with high dimensional mixed data, get deep features, do dynamic fusions, and adjust to different patients. thus, making it more versatile for dealing with different kinds of people and surgeries, like ones done on folks who have other illnesses at the same time or on complicated body parts like inside their chest – stuff that most single ways can't. The platform performs just as well with different groups of patients, which proves how strong it is. Such as the difference in recovery time between young people and old people, the difference in recovery time is due to the physiological factors such as a reduction in metabolism and a decrease in clearance of drugs in the body in older people that we know, which leads to a longer anesthesia recovery time. The same goes for minor discrepancies in accuracy among various types of surgery, like lobectomy vs esophagectomy – the differences probably come down to differences

in how much stress the surgery gives the person and what kind of medicine they need, more involved things cause stronger bad feelings which change your body. And these subgroup findings show this platform can fight clinical difference by taking many ways together.

But there's still some limitations to this platform which are worth taking into consideration. First off, the quality of the data largely hinges upon how precise the sensors are and how stable are the signals; anything that causes an interference with the signal inside the surgery such as the electric noise produced by the electrical surgical tools like the electrocoagulators or any kind of motion artifact caused for instance by the positioning of someone lying in surgery bed would need some sort preprocessing methods which might include things like adaptive filters or wavelet noise cancellation etc. Second, the computational complexity of sophisticated algorithms—particularly real-time inference-based deep learning models—may constrain system performance in resource-constrained clinical settings (e.g., operating rooms with limited processing power or bandwidth). This may cause delays and trigger alarms late. Future iterations may be able to solve this by using Edge computing devices for the processing and the other way is Model Compression. Model compression can reduce the computational power required but still have the same accuracy Compared with existing techniques such as single-frequency EEG monitoring (e.g., BIS), the application of multimodal platforms can greatly reduce postoperative delirium and intraoperative awareness by providing a comprehensive assessment of both cerebral and systemic physiological conditions. But it has the advantage of more hardware integration and calculation, which may increase the implementation price and technical training.

In clinic it is extremely advantageous to anesthetics for safe management and lessening of complication risks with better overall picture of patient's condition. It could use real-time hemodynamic and neurological data, to catch something like dropping blood pressure or not getting enough oxygen really quick, kind of like having extra helpers looking at your vitals in case anything goes wrong. However, the platform still has 3 big problems: integrating it smoothly with current healthcare systems (like getting electronic health records to play nicely together using HL7/FHIR), teaching doctors and nurses how to read all those different computer outputs, and being sure it's cheap enough to use – especially in places without lots of money where easy old machines like BIS are still commonly used. In the future, versions will get over these deficiencies by improving the efficiency of algorithms on edge computing devices and having good artifact detection mechanisms. In short, it is a big step ahead of the traditional way for sure, but to get it widely adopted, we need everyone - clinicians, engineers and healthcare administrators - working together to fix these practical problems.

5. Conclusions

The intelligent anesthesia depth monitoring platform created during this project uses the platform for monitoring anesthetize depth which was made from multimodal physiology signals. The anesthetic state can be estimated precisely when multiple physiological signals that include EEG, ECG, invasive blood pressure, and pulsatile wave are combined with the deep learning algorithm for feature extraction and fusion. The experimental results prove that this platform is outstanding at monitoring anesthesia depth, with a prediction probability over 0.95, a classification rate close to 0.89, and an average absolute error less than 4.5, greatly cutting down the dangers of both intraoperative awareness and too deep anesthesia, which greatly improves the surgical safety and postoperative recovery quality of patients. In future works, we will add more modalities such as Electromyography, signals for robustness, improve the algorithm design for better real-time process, and doing multicenters clinical trial to prove that this system can be used widely and reliably.

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