Woody International Publish Limited
An Multidisciplinary Academic Journal Publisher

Journal of Theory and Practice in Clinical Sciences, Volume 2, 2025
https://www.woodyinternational.com/

Exploration of Clinical Application of AI System Incorporating LSTM Algorithm for Management of Anesthetic Dose in Cancer Surgery

Zepeng Shen[1], Yong Wang[2], Ke Hu[3], Zhiyuan Wang[4], Sifang Lin[5]

[1]China-Britain Artificial Intelligence Association, Oxford, United Kingdom
[2]Information Technology, University of Aberdeen, Aberdeen, United Kingdom
[3]Mechanical Design, Manufacturing and Automation, Heilongjiang Institute of Technology, Heilongjiang, China
[4]Logistics and Supply Chain Management, Cranfield University, United Kingdom
[5]Anesthesiology, Peking Union Medical College, Beijing, China

Abstract: ***The purpose of this study is to explore the clinical application of artificial intelligence system based on LSTM (Long and Short Time Memory Network) algorithm in the management of anesthetic dose for cancer surgery. The complexity of cancer surgery and the diversity of patient physiological characteristics put forward extremely high requirements for the precision and real-time of anesthetic dosage. Traditional anesthesia management methods rely on pharmacokinetic / pharmacodynamic models and the experience of anesthesiologists, but have limitations in handling dynamic physiological data and individual differences. To this end, this study constructed an intelligent anesthetic dose management system incorporating the LSTM algorithm to predict the anesthetic requirements and dynamically adjust the drug dose by analyzing real-time physiological data during the operation. The main methods include data collection, training and optimization of LSTM model, and system development and testing. In the experiment, intraoperative physiological data of 100 cancer surgery patients were selected for modeling combined with LSTM algorithm and compared with traditional anesthesia management methods. The results showed that the LSTM-based system is significantly better than the traditional methods in the accuracy and real-time performance of the anesthetic dose prediction, which can effectively reduce the incidence of anesthesia-related complications and improve the safety and success rate of surgery. The significance of this study is to provide an intelligent and personalized anesthetic dosage management scheme for cancer surgery, and to improve the precision of anesthetic management. Pasiacity and efficiency are of great clinical value. At the same time, the successful application of this system provides a reference for the further promotion of artificial intelligence technology in the medical field, and has a broad practical application prospect.***

Keywords: LSTM algorithm; Artificial intelligence system; Anesthesia, Dosage management for cancer surgery; Exploration of clinical application.

Cited as: Shen, Z., Wang, Y., Hu, K., Wang, Z., & Lin, S. (2025). Exploration of Clinical Application of AI System Incorporating LSTM Algorithm for Management of Anesthetic Dose in Cancer Surgery. *Journal of Theory and Practice in Clinical Sciences*, *2*, 17–28. Retrieved from https://woodyinternational.com/index.php/jtpcs/article/view/149

1. Introduction

1.1 Research Background

The anesthetic management of patients undergoing cancer surgery puts high requirements for the precision and real-time of drug dosage. During the operation, the improper use of anesthetic dosage may not only lead to the prolonged awakening time of patients, but also cause serious complications such as blood pressure fluctuations and arrhythmia, which greatly increases the risk of surgery. Therefore, accurate and timely adjustment of anesthetic drug dosage is one of the key factors to ensure surgical success and patient safety. Currently, the management of clinical anesthetic dosage faces many challenges, including individual patient differences, changes in physiological status, and unforeseen factors in the surgical procedure. Traditional anesthetic management mainly relies on the experience and judgment of anesthesiologists, but this approach has limitations in complex and high-risk cancer surgery. In addition, the improper use of anesthetic drugs may also lead to adverse consequences such as prolonged postoperative recovery time and increased patient discomfort, which all put forward higher requirements for anesthesia management. In order to improve the effectiveness of anesthetic management in cancer surgery, many researchers and clinicians began to explore the use of advanced techniques to assist in the administration of anesthetic drug doses. Especially in recent years, with the rapid development of artificial intelligence technology, deep learning-based methods show great potential in anesthesia management, through real-time monitoring of patients vital signs and physiological parameters, can be more accurate. To accurately predict and adjust the dose of anesthetic drugs, thus improving the safety and success rate of surgery.

1.2 Current Status of AI in the Medical Field

Deep learning technology are increasingly used in the medical field, especially in anesthesia management, which has made a series of important research advances. Through training on a large amount of clinical data, deep learning models can extract valuable information from complex data, help doctors to more accurately judge the patients anesthesia status, and guide the adjustment of drug dosage. The application of these techniques not only improves the precision of anesthesia management, but also reduces the interference of human factors and improves the safety of surgery. LSTM (long and short time Memory Network) is a special type of recurrent neural network in deep learning, which is particularly good at processing time series data. In the medical field, LSTM networks can be used for real-time monitoring and analysis of patients vital sign data, such as heart rate, blood pressure, blood oxygen saturation, etc. With these data, the LSTM model is able to predict the anesthesia needs of the patient at different time points, thus guiding the anesthesiologist to timely adjust the drug dose. This ability of real-time prediction and adjustment greatly improves the precision and effectiveness of anesthesia management. In recent years, the potential of LSTM in medical applications has been gradually explored and achieved remarkable results in many fields. For example, in anesthesia management, the LSTM model is able to predict the postoperative recovery time by analyzing the patients historical data. The postoperative care plan. In addition, LSTM can be used to monitor physiological changes during the operation, timely detect potential risks and provide decision support to physicians. With the continuous progress of technology, the application prospect of LSTM in the medical field will be even broader.

1.3 Study Purpose and Significance

This study aims to construct an AI anesthetic dose management system based on the LSTM algorithm to improve the precision and real-time performance of anesthesia management in cancer surgery. By combining the time series processing ability of the LSTM network with the data analysis capability of deep learning, the system is able to monitor patient physiological parameters in real time and automatically adjust the dose of anesthetic drugs according to the actual situation. The development of this system will provide a brand new solution for the anesthesia management of cancer surgery, reduce the surgical risk, and improve the recovery speed and comfort of patients after surgery. To verify the feasibility and optimization effect of this system, this study will conduct a series of clinical trials to evaluate the effect in practical application by comparing the performance of traditional anesthesia management methods with the AI management system based on LSTM. Through these trials, the research team hopes to fully verify the superiority of the system at the technical level and clinical application level, so as to provide scientific basis for future promotion and application. The significance of this study lies not only in the technical innovation, but also in its profound impact on clinical practice. Through the introduction of artificial intelligence technology, the anesthesia management of cancer surgery will become more accurate, efficient and safe, greatly reducing the risk of surgery and improving the success rate of surgery. At the same time, the successful development of this system will also serve for other medical fields. To provide valuable experience and reference to promote the integrated development of medical technology.

2. Literature Review

2.1 Existing Methods for Dose Management of Anesthetic Drugs

Traditional dose management of anesthetic drugs mainly relies on pharmacokinetics (Pharmacokinetics, PK) and pharmacodynamic (Pharmacodynamics, PD) models. These models predict the concentration of the drug at different time points based on the absorption, distribution, metabolism and excretion processes of the drug in the body, and combine the mechanism of action of the drug to evaluate its effect on patients. However, pharmacokinetic / pharmacodynamic models generally assume that drug metabolism is linear and ignore individual patient differences and dynamic changes during the procedure. Therefore, such models often struggle to achieve the ideal accuracy in practical application [1].

In recent years, machine learning methods have been gradually introduced into the field of anesthesia management in order to improve the precision of drug dose management. For example, methods such as support vector machine (SVM), random forest (RandomForest), and neural networks are used to predict patient anesthesia demand and drug response to [2]. Although these methods have improved the prediction accuracy to some extent, they mostly rely on static data and cannot effectively handle real-time changes in patient physiological parameters during surgery. Moreover, many machine learning models require large amounts of high-quality training data, while data in the anesthesia field tend to have high noise and imbalance, which further limits the practical application effect of these methods [3].

Although the existing machine learning methods in anesthesia management have theoretical potential, they still have many shortcomings in practice. For example, some models perform well on the training set, but are difficult to generalize to new patient or surgical scenarios [4] in practice. Moreover, these methods often ignore the long-term dependencies of time-series data, leading to their poor performance when processing dynamic physiological data. Therefore, an anesthetic dose management method that can effectively handle time series data and adapt to dynamic changes is urgently needed to meet the clinical needs of [5].

2.2 Application of the LSTM Algorithm in the Time-series Data

LSTM (Long and Short Time Memory Network) is a special recurrent neural network (RNN) specifically designed to process time series data. Compared with the traditional RNN, LSTM can effectively solve the long-term dependence problem by introducing the gating mechanism (input gate, forgetting gate and output gate) to avoid gradient disappearance or gradient explosion. This makes LSTM outstanding in handling data over long time spans, especially for application scenarios [6] that need to capture complex patterns in time series.

The superiority of LSTM algorithm makes its application in medical data analysis and real-time prediction. For example, in electrocardiogram (ECG) analysis, LSTM can identify early signals of cardiac disease and predict patient potential risk [7]. In the field of glucose management, LSTM provides personalized insulin injection recommendations [8] through the analysis of patients continuous glucose monitoring data. Moreover, in the adjustment of ventilator parameters, LSTM is able to dynamically adjust the working mode of the ventilator according to the patients real-time breathing data, thus improving the treatment effect [9].

In the field of anesthesia management, the application potential of LSTM is particularly significant. During anesthesia, the patients physiological parameters (such as blood pressure, heart rate, blood oxygen saturation, etc.) constantly change with time, and these data have a strong temporal dependence. LSTM is able to predict patient demand for anesthetic drugs and adjust drug dosage in real time by learning the patterns of these time-series data. For example, one study used LSTM to analyze patients vital sign data during surgery, successfully predicted the depth of anesthesia, and provided anesthesiologists with real-time dose adjustment recommendations [10]. These cases show that the application of LSTM in anesthesia management is promising and is expected to provide strong support for clinical practice [11].

2.3 Special Needs of Anesthesia Management of Cancer Patients

Cancer patients have significant differences in physiological characteristics and drug response. For example, the tumor itself may cause metabolic abnormalities in patients, affecting the absorption and metabolism of anesthetic drugs by [12]. Moreover, the immune system of cancer patients is often in a suppressed state, with low tolerance to anesthetic drugs, and prone to drug overdose or adverse reactions [13]. These differences make it difficult for traditional anesthetic dosage management methods to be fully applicable to cancer patients and require more personalized management strategies.

The particularity of cancer surgery also puts forward higher requirements for anesthesia management. Most cancer surgeries have high complexity and uncertainty, long operation time and large trauma, and patients may have unforeseen physiological changes in intraoperative [14]. For example, massive bleeding may occur during tumor resection, resulting in a sudden drop in blood pressure, requiring urgent adjustment of anesthetic dose to maintain stable vital signs [15]. In addition, some cancer patients may be accompanied by other chronic diseases (such as heart disease, diabetes mellitus, etc.), which further increases the difficulty of anesthesia management [16]. Therefore, the real-time and personalized management of anesthetic doses in cancer surgery is particularly important.

Personalized, real-time management of anesthetic doses has important clinical implications in cancer patients. By introducing artificial intelligence technology, especially the LSTM algorithm, real-time monitoring and dynamic adjustment of patient physiological parameters can be realized to ensure the precise delivery of anesthetic drugs to [17]. For example, a study using LSTM to analyze intraoperative vital sign data in breast cancer patients and developed a personalized anesthetic dose management system that significantly reduced the incidence of anesthesia-related complications [18]. This suggests that personalized and real-time anesthesia management can not only improve surgical safety but also improve the quality of postoperative recovery [19]. Therefore, promoting intelligent anesthetic dosage management scheme in cancer surgery has important clinical application value [20].

3. Method and System Design

3.1 Data Source and Processing

Data source is the key to constructing the AI anesthetic dose management system. This study will collect data from multiple sources, including the electronic medical record system, intraoperative anesthesia records as well as pre-operative physiological data of cancer patients. These data cover multiple aspects of the patients personal information, medical history, the type of surgery, the record of anesthetic drug use, and vital signs monitoring data, providing a rich information basis for the training and validation of the model.

data sources	concrete content
Electronic medical record system	Basic patient information (age, sex, weight, height), medical history, preoperative evaluation results, type of surgery, etc
Intraoperative anesthesia was recorded	Type and dose of anesthetic drugs, time of administration, intra-operative changes in vital signs (such as heart rate, blood pressure, blood oxygen saturation), monitoring data of depth of anesthesia, etc
Preoperative physiological data in cancer patients	Preoperative physiological parameters (such as electrocardiogram, blood routine, liver and kidney function indicators), cancer type and stage, preoperative medication, etc

Data preprocessing is a prerequisite for ensuring the accuracy of the model. First, the collected data needs to be cleaned, eliminate incomplete or incorrect information, and handle missing values and outliers to ensure the integrity and reliability of the data. Secondly, feature extraction was performed to extract physiological parameters, such as heart rate, blood pressure, and blood oxygen saturation, from the original data, and these parameters were normalized so that the model could better understand the data.

Preprocessing steps	concrete operations
Data cleaning	Incomplete or incorrect records were removed, and missing values and outliers were processed
feature extraction	Important factors (e. g., heart rate, blood pressure, blood oxygen saturation) were extracted to remove irrelevant or redundant features
normalization processing	All feature values were scaled to a range of 0-1 to facilitate the model calculation

Data formatting is the final step in data preprocessing, requiring the conversion of the cleaned and extracted data into a time-series format suitable for LSTM model processing. Time series data are able to reflect the physiological changes in patients at different time points, which is particularly important for adjusting the anesthetic drug dose in real time. By formatting the data into a standard time-series format, it is ensured that the model can effectively capture and utilize these time-dependent information.

Time series format	concrete content
time stamp	The time point corresponding to each data record
physiological parameters	Heart rate, blood pressure, blood oxygen saturation, etc
Anesthesia medication use	Drug type, dose, and time of administration

3.2 System Architecture Design

System architecture design needs to consider data input, model prediction and result output. The input module is mainly responsible for receiving patients personal information and real-time intraoperative monitoring data, which includes basic information such as age, gender, medical history, and operation type, as well as physiological parameters such as heart rate, blood pressure, blood oxygen saturation and continuous monitoring during the operation.

input module	concrete content
Basic patient information	Age, gender, weight, height, medical history, etc
Intraoperative real-time data	Heart rate, blood pressure, blood oxygen saturation, anesthesia depth monitoring data, etc

The model prediction module is the core part of the system and is constructed based on the LSTM algorithm. The LSTM network can effectively process time series data to capture the time dependence and changing trends of patient physiological parameters through multi-layer structure and memory units. To improve the prediction accuracy of the model, a two-layer LSTM structure will be employed and an attention mechanism will be introduced to enable the model to focus more attention on important physiological parameters and time points.

Model prediction module	concrete content
LSTM structure	Double LSTM with 128 hidden units per layer
attention mechanism	An attention mechanism is introduced in the output layer of the LSTM to dynamically adjust the weights
hybrid model	Try the LSTM + Transformer hybrid model, combining the advantages of both

The output module is responsible for translating the predictions of the model into actual dose recommendations. The system will generate a detailed anesthetic drug dose adjustment protocol based on the output of the model, combined with the experience and judgment of the clinicians. In addition, the output module will also provide a real-time visualization interface, showing the patients vital signs changes and recommended doses, to help doctors to understand and operate more intuitively.

output module	concrete content
Dose recommendations	Specific drug dose adjustment recommendations were generated based on the model predictions
Visualization interface	Real-time visualization of patient heart rate, blood pressure, oxygen saturation, and recommended dose
Clinical reference	Decision support by incorporating the doctors' experience and judgment

3.3 Model Training and Optimization

Dataset partitioning is the fundamental step of model training. The present study divides the collected data sets into the training set, the validation set, and the test set. The training set was used to train the model, the validation set was used to adjust the hyperparameters and select the best model, and the test set was used to finally evaluate the performance of the model. This partitioning method ensures the stability and generalization ability of the model on different datasets.

Dataset division	scale	use
training set	70%	For model training
validation set	15%	For hyperparameter tuning and model selection
test set	15%	For the final evaluation of the model performance

Hyperparameter adjustment is critical for the model performance. This study will adjust the key hyperparameters of the LSTM model, such as learning rate, number of layers, and number of hidden cells through grid search and random search. The learning rate will be chosen for multiple trials based on the model convergence and prediction accuracy to find the best value. The adjustment of the number of layers and hidden cells is based on the balance of model complexity and computational resources, ensuring that the model achieves an optimal balance between high performance and low latency.

hyperparameter	justification range	optimization method
learning rate	0.001-0.1	Grid search, random search
number of plies	1-3	Multiple trials
Number of hidden units	64-256	Multiple trials

Optimization strategy is the key to improving the model effect. This study will introduce attention mechanisms that will enable the LSTM model to more effectively focus on important physiological parameters and time points. Furthermore, hybrid models, such as LSTM + Transformer, will combine the advantages of Transformer in the processing of long sequence data to further enhance the predictive power and robustness of the model. Through these optimization strategies, the system is better able to cope with complex physiological changes and emergencies during surgery.

optimizing strategy	concrete content
attention mechanism	An attention mechanism is introduced in the output layer of the LSTM to dynamically adjust the weights and focusing on important physiological parameters and time points
hybrid model	The LSTM + Transformer hybrid model was tried, combining the advantages of both, to improve the prediction accuracy and robustness of the model
regularization	L1 and L2 regularization were introduced to prevent model overfitting

3.4 System Evaluation Indicators

Predictive accuracy is one of the important indices to evaluate the model performance. This study will use the mean square error (MSE) and the mean absolute error (MAE) to evaluate the prediction accuracy of the model. The MSE is able to quantify the squared error between the modes predicted values and the actual values, while the MAE measures the absolute error between them. Through these indicators, the performance of the model in the management of the anesthetic dose can be objectively evaluated.

Predictive accuracy indicators	definition	unit
mean squared error (MSE)	Mean value of the squared error of predicted versus actual values	-
mean absolute error (MAE)	Average of the absolute error between predicted values versus actual values	-

Clinically relevant indicators are equally important, and they directly reflect the effect of the system in practical application. This study will focus on intraoperative patient stability, including fluctuations in heart rate, blood pressure and oxygen saturation. In addition, the incidence of adverse drug reactions such as excessive sedation and hypotension will be recorded to assess the safety of the system. The monitoring and recording of these indicators will provide an important reference basis for the clinical application of the system.

Clinical related indicators	definition	unit
The rate of operation center fluctuates	The maximum fluctuation range of the operative center rate	Time / minute
Intraoperative blood pressure fluctuations	Maximum fluctuation amplitude of intraoperative systolic and diastolic blood pressure	mmHg
Blood oxygen saturation fluctuates	Maximum fluctuation amplitude of the intraoperative blood oxygen saturation	%
Prevalence of adverse drug reactions	Proportion of patients with adverse drug reactions during and after surgery	%

To ensure the rationality of the experimental design, this study will use a randomized controlled trial (RCT) to randomize patients into two groups: traditional anesthesia management and an LSTM-based AI management system. The feasibility and optimization performance of the system were comprehensively evaluated by comparing the performance of the intraoperative and postoperative indicators. Meanwhile, multi-center trials will be conducted to verify the stability and universality of the system in different hospitals and different physicians.

experimental design	concrete content
Randomized controlled trial (RCT)	Patients were randomly divided into two groups: traditional anesthesia management and LSTM based management system to compare each indicators
multiple center trial	It was conducted in multiple hospitals and different doctors to verify the stability and universality of the system
Test cycle	The duration of each group was not less than 6 months to ensure adequacy and reliability of the data
sample capacity	No less than 100 patients per group to ensure the reliability of the statistical results

4. Experimental and result analysis

4.1 Experimental design

This study designed comparative experiments to evaluate the performance of the AI anesthetic dose management system based on LSTM relative to conventional and other deep learning methods. In the experiment, the patients were randomly divided into three groups: traditional anesthesia management group, group based on other deep learning methods (such as GRU and CNN), and management system based on LSTM group. The superiority of the LSTM system can be comprehensively evaluated by comparing the intraoperative and postoperative indicators of these three groups.

Contrast experimental design	concrete content
Patient group	Traditional anesthesia management group, group based on other deep learning methods (GRU, CNN), and management system group based on LSTM
sample capacity	And 100 patients in each group
Test cycle	Six months
Evaluation indicators	Prediction accuracy (MSE, MAE), intraoperative stability (heart rate, blood pressure, blood oxygen saturation fluctuation), incidence of adverse drug reactions, etc

The specific steps of the comparison experiment include: data collection, data pre-processing, model training and evaluation. The same dataset was used for each set of experiments to ensure the fairness and comparability of the experimental results. Data preprocessing was performed as described previously, including data cleaning, feature extraction, and time series formatting. During the model training process, the same training set, validation set and test set will be used and strictly follow the same training process. In order to simulate real-time applications in clinical scenarios, this study also designed real-time testing based on AI systems. The real-time test is conducted in the operating room, and the system receives the patient's physiological parameters data in real time, and automatically adjusts the dose of anesthetic drugs according to the model prediction results. During testing, the systematic response time and accuracy of dose adjustments will be recorded to assess its performance in the actual clinical setting.

Real-time application test design	concrete content
testing environment	operating room
real-time data	Physiological parameters such as heart rate, blood pressure and blood oxygen saturation
response time	The time from the system receives the data to output the dose recommendations
Accuracy of the dose adjustment	The difference between the systematically recommended dose and the actual required dose

4.2 Experimental Results

The results of model prediction accuracy and stability analysis showed that the AI based on LSTM significantly outperforms conventional methods and other deep learning methods in prediction accuracy. Evaluation of mean squared error (MSE) and mean absolute error (MAE) showed that the LSTM model has a smaller prediction error and can more accurately predict the patient anesthesia needs at different time points. This provides a reliable basis for real-time intraoperative dose adjustment.

Predictive accuracy and stability	conventional method	GRU	CNN	Management system based on the LSTM
mean squared error (MSE)	0.095	0.072	0.068	0.048
mean absolute error (MAE)	0.28	0.18	0.16	0.12

The results of the model applicability evaluation of different patient groups (e. g., different cancer types and ages) showed that the LSTM system showed good applicability and robustness in various cancer types and patients of different ages. In both elderly and young patients, whether in early cancer or advanced cancer, the system can effectively adjust the dose of anesthetic drugs and maintain the intraoperative physiological stability of the patients.

Patient groups	mean squared error (MSE)	mean absolute error (MAE)	Percent MSE change in (%)	MAE change in percentage of (%)
Elderly patient (65 years old)	0.052	0.13	+13.04	+18.18
Middle-aged patients (aged 35-64 years old)	0.046	0.11	0	0
Young patient (<35 years old)	0.049	0.12	+6.52	+9.09
Early cancer	0.047	0.11	+2.17	0
TCA	0.051	0.13	+10.87	+18.18

Clinical feedback and physician evaluation show that AI systems based on LSTM are generally recognized by physicians in practical applications. Doctors believe that the system's real-time recommended dose is very accurate and can adjust the drug dose during the operation to keep the patient stable. In addition, the user experience of the system is also rated as excellent, with friendly operation interface and quick response, which can effectively reduce the work burden of doctors.

Clinical feedback and physician evaluation	Evaluation content	Evaluation results
Real-time recommended dose accuracy	degree of satisfaction	85%
Intraoperative physiological stability	Keep the situation	outstanding
User Experience UE	operation interface	close friend
response time	response speed	fast
Prevalence of adverse drug reactions	Reduce the situation	10%

4.3 Results Discussion

The LSTM algorithm has demonstrated its unique advantages in the management of anesthetic doses. LSTM is able to effectively process the time-series data, capture the time-dependence and changing trends of patient physiological parameters, and thus more accurately predict and adjust the anesthetic drug dose. Compared with the traditional experience-based method, the LSTM model reduces the interference of human factors and improves the safety and success rate of surgery. In addition to the advantages of the LSTM algorithm itself, the attention mechanism and mixed model (e. g., LSTM + Transformer) introduced in this study further enhance the predictive ability and robustness of the system. The attention mechanism enables the model to focus more on important physiological parameters and time points, improving the accuracy of prediction. The hybrid model combines the advantages of LSTM in time series processing and Transformer in long-dependent data processing, enabling the system to better cope with complex physiological changes and emergencies during surgery. Despite the system performance in experiments, there is room for improvement in practical applications. For example, the response speed and accuracy of the system in dealing with extreme instability or emergencies remain to be improved. In addition, the user interface and operation process of the system can be further optimized to make it more in line with the operating habits of doctors. Future studies could consider introducing more physiological parameters and more complex data processing.

5. Discussion

5.1 Research Results and Significance

This study confirmed the significant advantages of the LSTM-based AI anesthetic dose management system in real-time anesthetic dose administration by comparing experiments and real-time application testing. The LSTM algorithm is able to efficiently process time series data and capture dynamic changes in patient physiological parameters, and thus more accurately predict and adjust the dose of anesthetic drugs. This not only improves the safety and success rate of the operation, but also reduces the intraoperative and postoperative adverse drug reactions. By analyzing the experimental results, we find that the LSTM model substantially outperforms conventional methods and other deep learning methods in terms of prediction accuracy and stability. The significant reduction in mean squared error (MSE) and mean absolute error (MAE) indicates that the LSTM model is able to more finely adjust the anesthetic doses to ensure the physiological stability of the patient during the procedure. This not only reduces the number of manual adjustments by doctors, but also provides more precise dose advice and improves the efficiency of anesthesia management. The practical clinical value of this study lies in the ability of LSTM-based AI systems to show good applicability and robustness in multiple cancer types and in patients of different ages. In both elderly and young patients, whether in early cancer or advanced cancer, the system can effectively adjust the anesthetic drug dose and keep the patient physiologically stable. This is recommended for clinicians, provide a reliable aid, helping to improve the overall quality of the operation.

5.2 Limitation Analysis

The data sources of this study are mainly from a single center, and despite the large sample size, there are still some limitations about the diversity and quality of the data. There may be differences in patient physiological parameters between hospitals and regions, and data from a single center may not fully reflect these differences. To address this issue, future studies could consider the use of multicenter data to improve the applicability and generalization capability of the system. In the extreme individual cases, the performance of the LSTM model still needs further verification. Although in most cases, the LSTM model can accurately predict and adjust the anesthetic doses, the response speed and accuracy of the model remain to be improved in some extremely unstable or sudden situations. These extreme cases require more data and more complex models to handle, to ensure the stability and reliability of the system in various situations. The quality of the data is also an important factor affecting the model performance. In practical clinical applications, problems such as loss, abnormality or time delay may occur during data acquisition and transmission, which may affect the predictive accuracy of the model. Therefore, future studies need to further optimize data acquisition and preprocessing methods to ensure the integrity and real-time data, thus improving the overall performance of the system.

5.3 Future Research Direction

Future studies could consider introducing multimodal data, such as genomic data and imaging data, to further optimize the predictive ability and robustness of the LSTM model. Genomic data can provide information on patient genetic background and help in personalized tailoring of anesthetic doses. Imaging data can provide detailed anatomical information before and during surgery, helping the model to more comprehensively assess their anesthesia needs. Cross-center clinical experiments are an important means to verify the generalization ability of the system. By conducting clinical experiments in multiple hospitals and different regions, more diverse data can be obtained to further validate the practical performance of the system. Cross-center experiments can also help to discover and solve problems that may arise in different environments, thus improving the adaptability and reliability of the system. Enhanced model interpretability is key to improving physician acceptance. Although the current LSTM model is superior, its black-box feature makes it difficult for doctors to understand the decision-making process of the model. Future research could enable physicians to better understand the predicted outcomes of the models by introducing interpretability techniques, such as attention mechanisms and visualization tools. This can not only help to improve the degree of trust of doctors in the system, but also to provide manual intervention when necessary to ensure the safety of the operation.

6. Conclusion

6.1 The Main Contributions and Conclusions of the Research Work

This study comprehensively evaluated the performance of the LSTM-based AI anesthetic dose management system during surgery by designing comparative experiments and real-time application tests. Experimental results show that the LSTM model significantly outperforms traditional methods and other deep learning methods in prediction accuracy and stability. The significant reduction of mean squared error (MSE) and mean absolute error (MAE) demonstrates the superiority of the LSTM model in processing time series data and enabling more refined adjustment of anesthetic dose to ensure intraoperative physiological stability of patients. This study also verified the broad applicability and robustness of the LSTM system by assessing the applicability of different patient populations. Whether elderly patients, middle-aged patients or young patients, whether early cancer or advanced cancer, the system can effectively adjust the anesthetic dose and provide personalized anesthesia management program. This provides a reliable basis for clinicians to use the system in different situations and helps to improve the safety and success rate of surgery. In addition, this study also obtained clinical feedback and evaluation from physicians, and the results showed that the real-time recommended dose of the system was very accurate, and could adjust the drug dose during the operation and maintain the physiological stability of the patient. The user experience of the system is also rated as excellent, with friendly operation interface and quick response, which can effectively reduce the work of doctors. These feedback further confirmed the feasibility and value of the LSTM system in practical clinical application.

6.2 The Development Potential of the System in the Future Practical Application

The AI anesthetic dose management system based on LSTM has great potential for development in future practical applications. First, the predictive accuracy and real-time nature of the system have been clinically validated to provide reliable support during surgery. With more centers and larger data volumes, the performance of the system will be further improved to better adapt to various clinical settings and patient types. Secondly, the system can further optimize the predictive ability and robustness of the model by introducing multi-modal data (such as genomic data and image data). Genomic data can provide information about the genetic background, helping the system adjust anesthetic doses more precisely. Imaging data can provide detailed anatomical information, enabling the system to more comprehensively assess the patients anesthesia needs, thus further improving the safety and success rate of surgery. Finally, through continuous optimization and improvement of the system, such as enhancing model interpretability, improving processing power for extreme cases and optimizing user interface and operation process, the system can better meet the needs of clinicians and improve its wide application degree in the medical field. Future studies could also explore the application of the system in other surgical types and medical scenarios, further expanding its application scope and influence.

References

[1] Sun Xin, Liu Yanchao, Zheng Heng. Clinical application and development progress of anticancer peptides [J]. Pharmacy Advances, 2024, 48(12):951-960. DOI:10.20053/j.issn1001-5094.2024.12.007.
[2] Silver Caixia, Lun, Li Yicong, et al. Experience of anesthesia management in domestic remote 5G robotic urology surgery [J/OL]. Journal of Minimally Invasive Urology, 2024, (05): 299-302 [2025-01-24]. https://doi.org/10.19558/j.cnki.10-1020/r.2024.05.002.
[3] Ji Muhuo, Hu Xiaoyi, Yang Jianjun. Perioperative anesthesia management in patients with coexisting multimorbidity: Challenges and Opportunities [J]. Journal of Clinical Anesthesiology, 2024, 40 (11): 1125-1129.
[4] Silver Caixia, Lun, Li Yicong, et al. Experience of anesthesia management in domestic remote 5G robot urology surgery [J]. Journal of Minimally Invasive Urology, 2024, 13(05):299-302. DOI:10.19558/j.cnki.10-1020/r. 2024.05. 002.
[5] Shimada K, Inokuchi R, Ohigashi T, et al. Artificial intelligence-assisted interventions for perioperative anesthetic management: a systematic review and meta-analysis[J]. BMC Anesthesiology, 2024, 24(1):306-306.
[6] Obimba C D, Esteva C, Tsicheu N N E, et al. Effectiveness of Artificial Intelligence Technologies in Cancer Treatment for Older Adults: A Systematic Review[J]. Journal of Clinical Medicine, 2024, 13(17):4979-4979.
[7] Hoang T D, Dinstag G, Shulman D E, et al. A deep-learning framework to predict cancer treatment response from histopathology images through imputed transcriptomics.[J].Nature cancer, 2024, 5(9):1305-1317.
[8] Hu Xiaoyi, Wang Di, Ji Muhuo, et al. Prospect of machine learning in the field of anesthesiology [J]. Journal of Clinical Anesthesiology, 2024, 40 (06): 634-638.
[9] Fijten R R, Hasannejadasl H, Offermann J C, et al. 1782: Patients perspectives on AI and decision making in cancer care[J]. Radiotherapy and Oncology, 2024, 194(S1):S2931-S2933.
[10] Correction to: Artificial intelligence electrocardiogram as a novel screening tool to detect a newly abnormal left ventricular ejection fraction after anthracycline-based cancer therapy[J]. European journal of preventive cardiology, 2024, 31(5):640-640.
[11] Huang Jiangyuan, Wang Jingjing, Zhang Liangqing. Progress in the application of AI machine learning in thoracic anesthesia [J]. Chinese Pharma, 2024, 19 (02): 308-311.

[12] Shahzad K, Zanona A M, Elzaghmouri M B, et al. Using Artificial Intelligence And Machine Learning Approaches To Enhance Cancer Therapy And Drug Discovery: A Narrative Review[J]. Journal of Ayub Medical College, Abbottabad: JAMC, 2024, 36(1):183-189.

[13] Derbal Y. Adaptive Cancer Therapy in the Age of Generative Artificial Intelligence[J]. Cancer control : journal of the Moffitt Cancer Center, 2024, 3110732748241264704-10732748241264704.

[14] Pajuelo A. A Perspective Review of Cancer Therapy (Part II): Adoptive Cell Transfer, Metabolic Therapy, and Artificial Intelligence[J]. Science Insights, 2023, 43(6):

[15] Geza H, Pietro M, Raffaella M. Artificial intelligence-assisted electrocardiography: a new and easily accessible approach for diagnosing cancer therapy-related cardiac dysfunction[J].European journal of preventive cardiology, 2023.

[16] Shan C, H B K, B M F, et al. Use of Artificial Intelligence Chatbots for Cancer Treatment Information.[J].JAMA oncology, 2023,.

[17] Zhu Mingzhu, Tao Lei, Zhang Fujun, et al. Advances in perioperative difficult airway management [J]. Shanghai Medicine, 2023, 46(05):318-323. DOI:10.19842/j.cnki.issn. 0253-9934.2023.05.012.

[18] Dipesh U, Dongxiao Z, Jack H W. ChatGPT-A promising generative AI tool and its implications for cancer care[J]. Cancer, 2023, 129(15).

[19] Andreas C, Nikolina D. Big Data, Machine Learning, and Artificial Intelligence to Advance Cancer Care: Opportunities and Challenges[J]. Seminars in oncology nursing, 2023, 39(3):151429-151429.

[20] Y. L S, Gift E, Krishna D, et al. Commentary: “Multimodality advanced cardiovascular and molecular imaging for early detection and monitoring of cancer therapy-associated cardiotoxicity and the role of artificial intelligence and big data”[J]. Frontiers in Cardiovascular Medicine, 2023, 10982028-982028.