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Research article

Artificial intelligence algorithms for predicting post-operative ileus after laparoscopic surgery

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ABSTRACT

Objective: By constructing a predictive model using machine learning and deep learning technologies, we aim to understand the risk factors for postoperative intestinal obstruction in laparoscopic colorectal cancer patients, and establish an effective artificial intelligence-based predictive model to guide individualized prevention and treatment, thus improving patient outcomes.

Methods: We constructed a model of the artificial intelligence algorithm in Python. Subjects were randomly assigned to either a training set for variable identification and model construction, or a test set for testing model performance, at a ratio of 7:3. The model was trained with ten algorithms. We used the AUC values of the ROC curves, as well as accuracy, precision, recall rate and F1 scores.

Results: The results of feature engineering composited with the GBDT algorithm showed that opioid use, anesthesia duration, and body weight were the top three factors in the development of POI. We used ten machine learning and deep learning algorithms to validate the model, and the results were as follows: the three algorithms with best accuracy were XGB (0.807), Decision Tree (0.807) and Neural DecisionTree (0.807); the two algorithms with best precision were XGB (0.500) and Decision Tree (0.500); the two algorithms with best recall rate were adab (0.243) and Decision Tree (0.135); the two algorithms with highest F1 score were adab (0.290) and Decision Tree (0.213); and the three algorithms with best AUC were Gradient Boosting (0.678), XGB (0.638) and LinearSVC (0.633).

Conclusion: This study shows that XGB and Decision Tree are the two best algorithms for predicting the risk of developing ileus after laparoscopic colon cancer surgery. It provides new insight and approaches to the field of postoperative intestinal obstruction in colorectal cancer through the application of machine learning techniques, thereby improving our understanding of the disease and offering strong support for clinical decision-making.

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1. Introduction

At present, radical resection is the only way to cure colorectal cancer. With advancements in medical technology, laparoscopic surgery is a mature surgical technique, and laparoscopic colorectal-carcinoma surgery has been widely used by clinical doctors. However, studies have shown that ileus still occurs after laparoscopic surgery in patients with colorectal cancer [1]. Some data implies that 3%–30% of patients undergoing abdominal surgery suffer from postoperative ileus (POI) complications, which manifests as the absence of bowel movements, nausea, vomiting, abdominal distention and intolerance to oral intake [2,3]. The occurrence of ileus not only causes patients to suffer, but also prolongs hospital stays, and threatens these patients' prognosis [4]. However, there is no scientific and unified model for predicting ileus in clinical practice. Therefore, a comprehensive understanding of the risk factors for ileus after laparoscopic surgery in patients with colorectal cancer, and the establishment of an effective model, are crucial for guiding individualized prevention and treatment for these patients, and improving their prognosis.

There is an increasing amount of research on predicting postoperative intestinal obstruction. Studies have shown that the construction of a nomogram can be used to predict the occurrence of long-term intestinal obstruction in gastric cancer patients undergoing gastrectomy [5]. Similarly, charts have been used to assess the likelihood of long-term intestinal obstruction following partial bowel resection in patients with Crohn's disease [6]. Additionally, a chart based on preoperative albumin levels has been shown to effectively predict the risk of postoperative intestinal obstruction in gastrointestinal surgery [7]. Furthermore, research has indicated that combining factors such as age, hypoalbuminemia, and surgical difficulty can provide more accurate predictions for long-term intestinal obstruction following laparoscopic low anterior resection for rectal cancer [8]. However, most existing studies on early postoperative intestinal obstruction (POI) have focused on using biomarkers or charts for prediction, while the application of artificial intelligence in the field of POI has been limited. In fact, artificial intelligence techniques offer significant advantages in handling large volumes of complex data and achieving accurate predictions. Therefore, further exploration of the application of artificial intelligence in building and optimizing POI prediction models is worthwhile.

Risk prediction plays an important role in clinical decision-making, and the introduction of artificial intelligence (AI) algorithms offers exciting prospects for improving risk assessment and developing targeted predictive strategies. Machine learning algorithms in artificial intelligence play an important role in medical data analysis, and can be used to identify the characteristics of related variables [9–13]. Research results have confirmed the validity of using machine learning algorithms to predict postoperative pulmonary complications in patients with acute diffuse peritonitis [14]. Studies have also shown that machine learning can predict the recurrence of gastric cancer among patients after surgery [15]. It can also predict intraoperative bleeding in patients undergoing hepatectomy [16].Furthermore, studies have indicated that Connected Convolutional Networks could be reliable diagnostic tools for various pulmonary diseases [17]. Similarly, deep learning has shown great potential in combining chest CT scans and X-ray imaging to conduct in-depth analysis of pulmonary diseases [18]. Moreover, machine learning can integrate MR imaging and clinical data to effectively classify dementia symptoms [19]. At the same time, transfer learning models have achieved significant progress in combining X-ray detection for COVID-19 patients [20]. Additionally, ensemble learning performs exceptionally well in identifying patients with polycystic ovary syndrome [21]. In conclusion, artificial intelligence holds tremendous potential in the fields of clinical diagnosis and prediction [22]. However to date, no studies have used machine learning or deep learning techniques to predict POI in laparoscopic colon cancer surgery.

Therefore, this study comprehensively analyzes the relevant factors of postoperative intestinal obstruction in laparoscopic colorectal cancer surgery using machine learning techniques. By constructing a predictive model using machine learning and deep learning technologies, we aim to understand the risk factors for postoperative intestinal obstruction in laparoscopic colorectal cancer patients, and establish an effective artificial intelligence-based predictive model to guide individualized prevention and treatment. By utilizing machine learning techniques, this study provides new insight and approaches to the research field of postoperative intestinal obstruction in colorectal cancer, improving our understanding of the disease and offering strong support for clinical decision-making.

2. Methods

2.1. Database analysis

We obtained data on POI after laparoscopic colorectal-carcinoma surgery from the BioStudies (public) database. The BioStudies database contains a description of the biological research, links to these research data in the EMBL-EBI or other external databases, and data that is not appropriate for the EMBL-EBI structured archive. The original link related to this research is https://www.ebi.ac.uk/biostudies/studies/S-EPMC5757986?. query = S-EPMC5757986. We conducted retrospective analysis on data from patients aged 18 years old and above who had undergone laparoscopic colorectal surgery for malignant lesions in the BioStudies (public) database. The exclusion criteria were any patients undergoing concurrent surgery other than laparoscopic colorectal surgery, or conversion to open surgery, or robot-assisted laparoscopic colorectal surgery, as well as parenteral nutrition. POI was defined as the absence of bowel distention and/or defecation 3 days after surgery, or oral intolerance, with abdominal radiographs showing intestinal and/or colon dilatation. In total, 637 patients were included.

2.2. Comparative analysis of basic data

We analyzed the data in R. Categorical data were expressed as cases (%) and compared using a $\chi 2$ test. The quantitative data were expressed as $\bar{x} \pm s$, and comparison among groups was conducted with a *t*-test if it had homoscedasticity, and a corrected *t*-test if it did not have homoscedasticity.

2.3. Machine learning methods

We constructed the artificial intelligence algorithm model in Python. Data preprocessing consisted of inputting explanatory variables, processing laboratory data and missing data, and standardizing the data. Subjects were randomly assigned at a ratio of 7:3 to either a training set for variable identification and model construction, or a test set for testing model performance. Details on these variables are shown in Supplementary Table 1. We analyzed the relationship between each variable and POI using a Pearson correlation. Next, we used the GBDT machine learning algorithm to evaluate the weight of each variable accounting for POI.

First stage: Training model.

We used ten algorithms—Logistic Regression, Decision Tree, Gradient Boosting (GBDT), Linear SVC (Linear Support Vector Classification), XGB (Extreme gradient boosting) , Neural Decision Tree , knn (K-nearest neighbors), adab (AdaBoost), LSTMLSTM (Long Short - Term Memory), CNNLSTM (Convolutional Neural Network + Long Short - Term Memory)—to train and prepare the model. Logistic regression is a classic algorithm, a machine learning method used to solve classification problems and estimate the likelihood of a given event. It has the characteristics of simplicity, parallelism and strong explanatory power. Decision tree is an important classification and regression method in data mining. It is a predictive analysis model expressed in tree structure (either a binary or multi-branch tree). In the past ten years. The basic structure of GBDT is a forest composed of decision trees, and the learning method is gradient lifting. Specifically, as an integrated model, GBDT predicts by adding up the results of all subtrees. GBDT generates the whole forest by generating decision subtrees one by one, and the process of generating a new subtree is to construct a new subtree by using the residual between the sample label value and the current forest prediction value. Linear SVC is a generalized linear classifier that classifies data in a binary mode according to supervised learning. The concept underlying KNN algorithms is that a sample is the most similar to K samples in the data set. If most of these K samples belong to a certain category, the sample also belongs to this category. LSTM is a time recurrent neural network. Convolutional neural networks (CNN) are a kind of feedforward neural network with deep structure and convolution calculation.

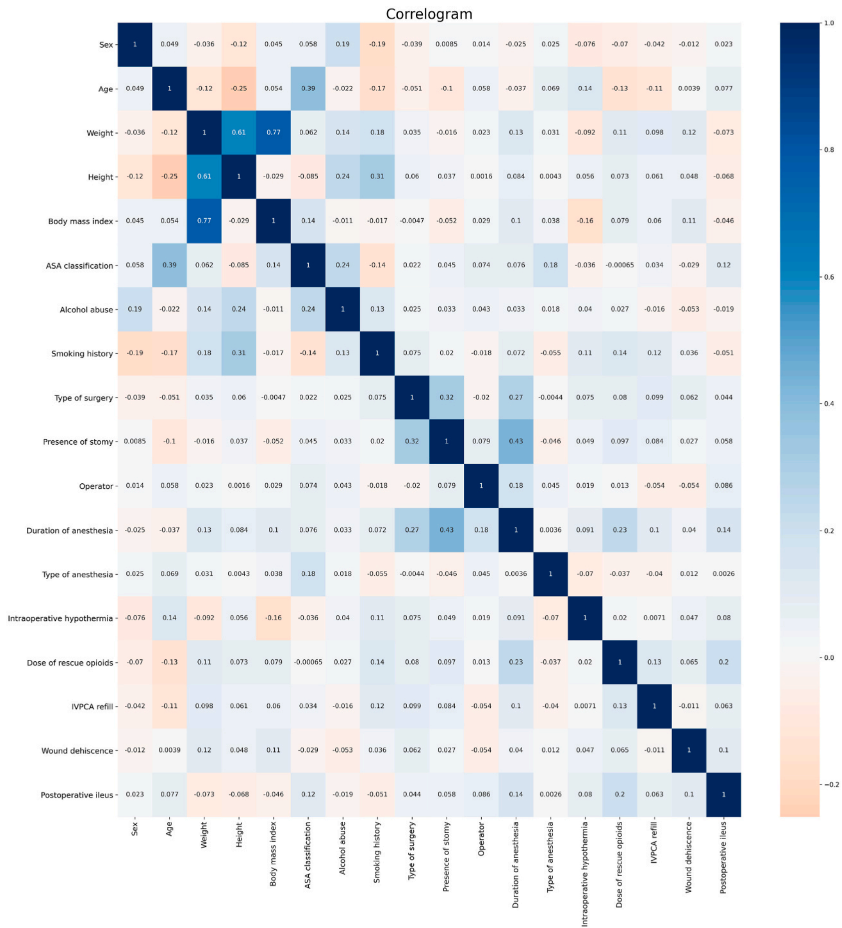

Fig. 1. Correlation between various clinical variables.

Regarding the parameters used in the model, we used both manual and grid tuning methods.

Second stage: Validating the model.

We verified the performance of these machine learning models trained on the training group in the test group data. At the same time, we used five-fold cross-validation as an internal validation.

Third stage: Evaluation model.

For the performance evaluation, we used the ROC curves' AUC values, as well as accuracy, precision, recall rate and F1 scores. AUC is the area under the ROC curve, which is used to evaluate classification models' performance. The ROC curve represents the relationship between true the positive rate and the false positive rate. The closer the AUC value is to 1, the better the model performance, in other words, it can better differentiate between positive and negative samples. Accuracy: Accuracy is the proportion of correctly predicted samples among all samples, indicating the model's prediction consistency with actual results. The higher the accuracy, the more consistency there is between the model prediction and the actual results. Precision: Precision is the proportion of truly positive samples among those predicted to be positive. Precision measures model prediction accuracy for positive samples. High precision indicates that a model can minimize false positives by correctly identifying positive samples. Recall Rate: Recall rate is the proportion of actual positive samples that a model correctly predicts to be positive. Recall rate measures the model's recall rate for positive samples. High recall rate indicates that the model can minimize false negatives by correctly identifying positive samples. F1 Score: F1 score is the harmonic mean of precision and recall, which considers both accuracy and recall rate. The closer the F1 score is to 1, indicating that the model can balance precision and recall rates, the better its prediction performance.

The methodological flow chart of this study is shown in Supplementary Fig. 1. The related literature review table is shown in Supplementary Table 2.

3. Results

A total of 122 patients with postoperative intestinal obstruction were included in this study, and the incidence rate was 19.15%. In total, 637 patients were included.

3.1. Correlation analysis and weight-account analysis for POI

Correlation analysis showed a positive correlation between anesthesia duration, anesthesia grade, opioid use and POI, and a negative correlation between body weight and ileus (Fig. 1). The results of feature engineering composited with the GBDT algorithm showed that opioid use, anesthesia duration, and body weight were the three primary factors for the development of POI (Fig. 2).

3.2. Machine learning results in the training set for predicting POI

The three algorithms with the highest accuracy were XGB (0.858), CNNLSTM (0.856), and adab (0.843). These algorithms were able to accurately predict POI on the training set. The two algorithms with the highest precision were GradientBoosting (1.000) and XGB (0.958). These algorithms have higher accuracy in predicting positive cases, minimizing the misclassification of negative cases as positive cases. The two algorithms with the highest recall were adab (0.388) and CNNLSTM (0.341). This means that these algorithms were able to capture the true POI cases in the training set. The two algorithms with the highest F1 score were adab (0.485) and CNNLSTM (0.475). F1 score accounts for precision and recall rates, indicating that these algorithms performed well in balancing accuracy and recall rates. The two algorithms with the highest AUC were XGB (0.942) and GradientBoosting (0.905). The AUC values measure the model's classification ability at different thresholds, with higher AUC values indicating better performance on the training set (Fig. 3 and Table 1).

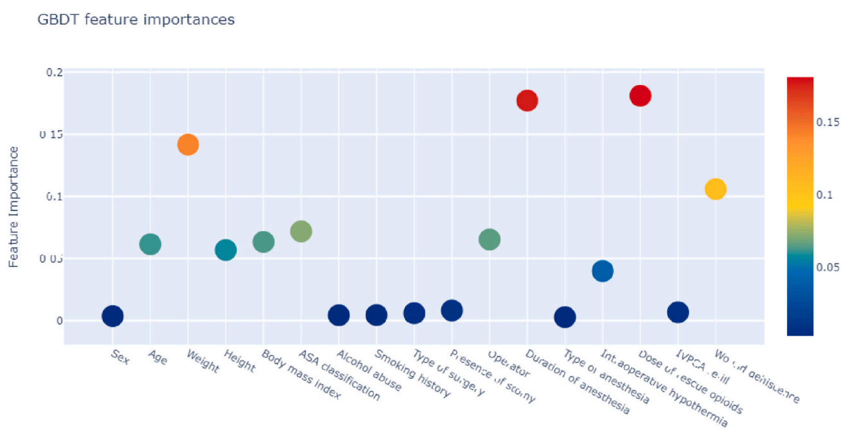

Fig. 2. Weight analysis of each variable accounting for POI.

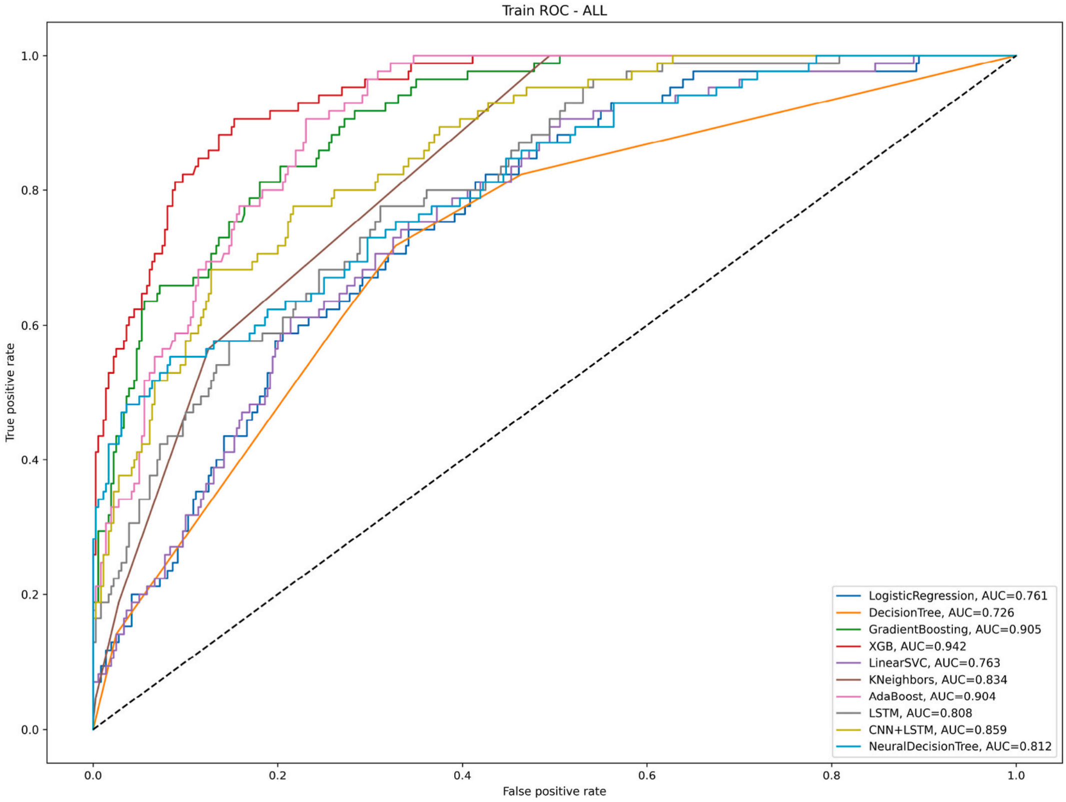

Fig. 3. AUC values for the ten artificial intelligence algorithms in the training group. Notes: Logistic Regression, Decision Tree, Gradient Boosting, Linear SVC (Linear Support Vector Classification), XGB (Extreme gradient boosting) , Neural Decision Tree , knn (K-nearest neighbors), adab (AdaBoost), LSTM (Long Short - Term Memory), CNNLSTM (Convolutional Neural Network + Long Short - Term Memory).

Table 1
Artificial intelligence algorithm results for POI prediction by the training group.

model_name	AUC	Accuracy	Precision	Recall	F1 score
LogisticRegression - Train	0.761	0.816	0.588	0.118	0.196
DecisionTreeClassifier - Train	0.726	0.816	0.571	0.141	0.226
GradientBoostingClassifier - Train	0.905	0.838	1.000	0.153	0.265
XGBClassifier - Train	0.942	0.858	0.958	0.271	0.422
LinearSVC - Train	0.763	0.820	0.778	0.082	0.149
knn - Train	0.834	0.822	0.615	0.188	0.288
adab - Train	0.904	0.843	0.647	0.388	0.485
LSTM - Train	0.808	0.834	0.739	0.200	0.315
CNNLSTM - Train	0.859	0.856	0.784	0.341	0.475
NeuralDecisionTree - Train	0.812	0.809	0.000	0.000	0.000

Notes: Logistic Regression, Decision Tree, Gradient Boosting, Linear SVC (Linear Support Vector Classification), XGB(Extreme gradient boosting) , Neural Decision Tree , knn (K-nearest neighbors), adab (AdaBoost), LSTM (Long Short - Term Memory), CNNLSTM (Convolutional Neural Network + Long Short - Term Memory).

3.3. Machine learning results in the test set for predicting POI

The three algorithms with highest accuracy were XGB (0.807), Decision Tree (0.807), and Neural DecisionTree (0.807). These algorithms also performed well on the test set, indicating good model performance on unknown data. The two algorithms with the highest precision were XGB (0.500) and Decision Tree (0.500). These algorithms maintained high accuracy in predicting positive cases. The two algorithms with the highest recall were adab (0.243) and Decision Tree (0.135). Although these algorithms performed slightly worse on the test set compared to the training set, they still exhibited good performance. The two algorithms with the highest F1 scores were adab (0.290) and Decision Tree (0.213). This indicates that these algorithms had a balanced performance on the test set, improving both accuracy and recall rates. The three algorithms with the highest AUC were Gradient Boosting (0.678), XGB (0.638), and LinearSVC (0.633). Higher AUC values indicated better performance for the model on the test set (Fig. 4 and Table 2).

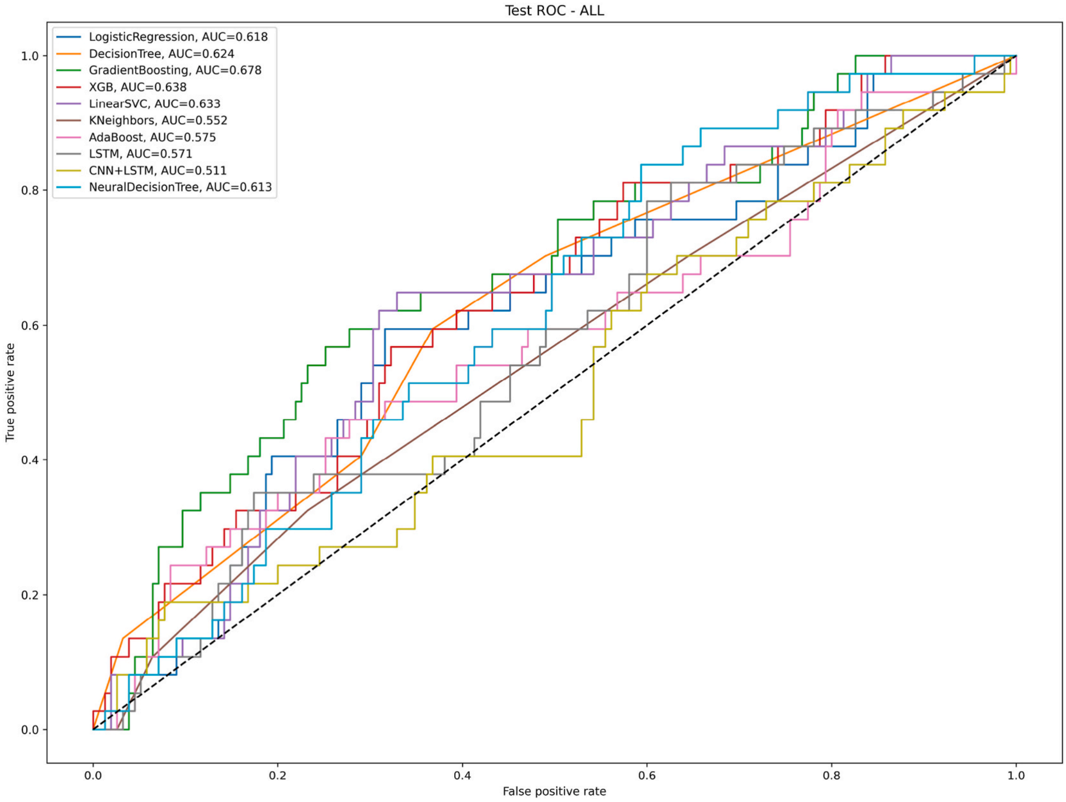

Fig. 4. AUC values for the ten artificial intelligence algorithms in the test group. Note: Logistic Regression, Decision Tree, Gradient Boosting, Linear SVC (Linear Support Vector Classification), XGB (Extreme gradient boosting) , Neural Decision Tree , knn (K-nearest neighbors), adab (AdaBoost), LSTM (Long Short - Term Memory), CNNLSTM (Convolutional Neural Network + Long Short - Term Memory).

Table 2
Results of artificial intelligence algorithm for POI prediction, by test group.

model_name	AUC	Accuracy	Precision	Recall	F1 score
LogisticRegression - Test	0.618	0.786	0.300	0.081	0.128
DecisionTreeClassifier - Test	0.624	0.807	0.500	0.135	0.213
GradientBoostingClassifier - Test	0.678	0.781	0.222	0.054	0.087
XGBClassifier - Test	0.638	0.807	0.500	0.108	0.178
LinearSVC - Test	0.633	0.802	0.400	0.054	0.095
knn - Test	0.552	0.776	0.286	0.108	0.157
adab - Test	0.575	0.771	0.360	0.243	0.290
LSTM - Test	0.571	0.781	0.222	0.054	0.087
CNNLSTM - Test	0.511	0.781	0.273	0.081	0.125
NeuralDecisionTree - Test	0.613	0.807	0.000	0.000	0.000

Notes: Logistic Regression, Decision Tree, Gradient Boosting, Linear SVC (Linear Support Vector Classification), XGB(Extreme gradient boosting) , Neural Decision Tree , knn (K-nearest neighbors), adab (AdaBoost), LSTM (Long Short - Term Memory), CNNLSTM (Convolutional Neural Network + Long Short - Term Memory).

Therefore, in terms of overall performance, the AI algorithms that achieved superior performance in both the training and the testing groups were the XGB and Decision Tree algorithms.

4. Discussion

Colorectal cancer is a common malignant tumor of the gastrointestinal tract, and its incidence has been on the rise in recent years [23]. POI is one of the major complications after colorectal cancer surgery. POI after colorectal cancer surgery can lead to water-electrolyte disorder and acid-base imbalance, increasing patients' pain, prolonging hospitalization, and even leading to death in serious cases. Therefore, early identification of POI risk factors and targeted individualized treatment plans are particularly important. In this study, we found that anesthesia duration, use of opioids, and body weight were the three main factors associated with the development of ileus after laparoscopic colon cancer surgery. These results showed that XGB and Decision Tree were the two algorithms with the best general performance for predicting the risk of developing ileus after laparoscopic colon cancer surgery.

Several studies have shown a strong association between anesthesia and POI. Other studies have shown that epidural anesthesia and intraoperative blood transfusion can reduce the incidence of POI [24]. It has also been shown that surgery duration and blood loss volume are independent risk factors for POI in patients undergoing posterior thoracolumbar fusion [25]. Similarly, it has been shown that general anesthesia combined with epidural anesthesia plays an important role in rapid surgery, reducing the impairment of antitumor immune response associated with surgical stress, and accelerating the recovery of intestinal function after surgery [26]. The results of our study also support this conclusion.

Several studies have also shown a strong association between opioids and POI. Research shows that intravenous opioid therapy is significantly correlated with POI and prolonged hospital stay [26]. There are also studies showing that the use of opioids in hospitals can increase the incidence of postoperative paralytic ileus [27]. In addition, studies have revealed that intraoperative opioid remifentanil dosage is an independent risk factor for the development of ileus after oblique lateral interbody fusion [28]. The results of our study also support this conclusion.

Several studies have also shown a strong association between body weight and POI. Some studies have shown that smoking and weight loss are important influencing factors for POI [29]. It has also been shown that increasing age and BMI are associated with the presence of POI in patients who have undergone radical cystectomy for bladder cancer [30]. Our study also supports this conclusion.

The application of artificial intelligence in medicine has a wide range of prospects. It has been reported that machine learning can be used to predict the recurrence of stage IV colorectal cancer [31]. Machine learning models can also predict readmission after colorectal surgery [32]. Additionally, they have been shown to predict the amount of bleeding in patients undergoing liver cancer resection [33]. Similarly, we can evaluate the quality of blood perfusion in laparoscopic colorectal surgery using machine learning [34]. As a clinically novel tool, artificial intelligence may improve our clinical decision-making process and guide the management of these patients, raising the quality of life for postoperative patients. In our study, we also used artificial intelligence algorithms to predict intestinal obstruction after laparoscopic surgery.

Lessons learned: During the research process, it is important to clean and preprocess clinical data and transform it into a form suitable for machine learning algorithms. Algorithm selection and optimization: In this study, we tried various machine learning algorithms such as logistic regression, support vector machines, and random forest to build prediction models. When comparing different models' prediction performance, the most suitable algorithm needs to be selected based on the actual problem and data characteristics. At the same time, optimizing model parameters also improves the model's prediction accuracy. It is also necessary to continually adjust model parameters and optimize model structure to improve the model's stability and generalizability.

Impact on theory and practice: This study provides a new research method for predicting postoperative intestinal obstruction in colorectal cancer, applying machine learning technology to clinical practice. This will help clinicians to better understand patients' risk status and provide individualized prevention and treatment measures. In addition, the results of this study may also provide reference for predicting other postoperative complications.

This study has several limitations. First, it is a retrospective study and it may still be lacking some relevant variables, such as other complications during surgery and relevant genetic testing results, as well as intestinal handling and manipulation during surgery and the resulting release of local inflammatory mediators. Second, in future studies, it would be helpful to break POI types into subgroups, as the means of prevention and treatment for different types of ileus also vary.

Follow-up steps: In future research, we will continue to optimize the prediction model and improve its accuracy to better guide clinical practice. Additionally, we will explore more effective machine learning methods to apply in a wider range of medical fields. Meanwhile, we will engage in multi-center collaborations, expand sample sizes, and validate the generalizability and reliability of our study results.

Comparison with similar scoring models in the literature: 1). Methodological differences: Unlike nomogram methods, our work primarily employs machine learning and deep learning algorithms to construct predictive models. These two approaches differ from traditional scoring models and offer greater flexibility and predictive capabilities. By leveraging the characteristics of these algorithms, we can handle more complex data structures and improve the accuracy and generalization capabilities of the predictive model. 2). Prediction performance comparison: Although nomogram methods are widely used in clinical practice and have a certain degree of interpretability, their prediction performance may be limited compared to machine learning methods. Machine learning algorithms can better utilize large-scale data and nonlinear relationships, thus improving the accuracy and generalizability of the prediction model. Therefore, our work should achieve higher accuracy and prediction capabilities in predicting postoperative intestinal obstruction, thereby providing more accurate guidance for individualized prevention and treatment. 3). Explanability and practical application: While machine learning methods have advantages in prediction performance, they are difficult to interpret. In contrast, nomogram methods have interpretability, allowing for the direct quantification and comparison of the contributions of different factors to the results. Because of this feature, nomogram methods are advantageous in clinical decision-making. However, in our future work we still hope to establish machine learning models to improve prediction accuracy and provide predictive tools for clinicians in practical applications. Moreover, in our research, we will also strive to explain model results to promote the application and understanding of the predictive model.

5. Conclusion and future work

In this study, we have integrated and evaluated multiple machine learning and deep learning algorithms. Our findings show that XGB and Decision Tree are the two algorithms with the best performance for predicting the risk of developing ileus after laparoscopic colon cancer surgery. Our model has good predictive performance and clinical value, and can assist in clinicians' preliminary assessment of ileus occurring after laparoscopic colon cancer surgery. This will enable them to identify high-risk groups early, and adopt more precise prevention plans for individualized treatment.

In the future, we will conduct a prospective multi-center cohort study, collect more types of patients with postoperative intestinal obstruction, and establish a relevant big data platform. Then, using the big data analysis method, we will establish an intelligent early warning system for postoperative intestinal obstruction, classify and manage and appropriately intervene with groups at high-risk of POI, and establish health records for patients with POI. In this way, we can pay timely attention to, and appropriately intervene with, prognosis and treatment, for individuals with POI. We can also provide new clinical management paths and inform decisions for POI.

Ethics statement

The study was approved by the Ethics Committee of the First Affiliated Hospital of Zhengzhou University (2020-KY-378). As the study was a secondary retrospective analysis using a database, the ethics Committee exempted the informed consent form of the patients.

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None.

Availability of data and materials

Data is available at BioStudies database (https://www.ebi.ac.uk/biostudies/studies/S-EPMC5757986?query=S-EPMC5757986) [35].

CRediT authorship contribution statement

Cheng-Mao Zhou: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **HuiJuan Li:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Qiong Xue:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Jian-Jun Yang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yu Zhu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e26580.

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