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Original Article

Development and comparison of machine-learning models for predicting prolonged postoperative length of stay in lung cancer patients following video-assisted thoracoscopic surgery

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ABSTRACT

Objective: This study aimed to develop models for predicting prolonged postoperative length of stay (PPOLOS) in lung cancer patients undergoing video-assisted thoracoscopic surgery (VATS) by utilizing machine-learning techniques. These models aim to offer valuable insights for clinical decision-making.

Methods: This retrospective cohort study analyzed a dataset of lung cancer patients who underwent VATS, identifying 25 numerical features and 45 textual features. Three classification machine-learning models were developed: XGBoost, random forest, and neural network. The performance of these models was evaluated based on accuracy (ACC) and area under the receiver operating characteristic curve, whereas the importance of variables was assessed using the feature importance parameter from the random forest model.

Results: Of the 6767 lung cancer patients, 1481 patients (21.9%) experienced a postoperative length of stay of > 4 days. The majority were male (4111, 60.8%), married (6246, 92.3%), and diagnosed with adenocarcinoma (4145, 61.3%). The Random Forest classifier exhibited superior prediction performance with an area under the curve (AUC) of 0.792 and ACC of 0.804. The calibration plot revealed that all three classifiers were in close alignment with the ideal calibration line, indicating high calibration reliability. The five most critical features identified were the following: surgical duration (0.116), age (0.066), creatinine (0.062), hemoglobin (0.058), and total protein (0.054).

Conclusions: This study developed and evaluated three machine-learning models for predicting PPOLOS in lung cancer patients undergoing VATS. The findings revealed that the Random Forest model is most accurately predicting the PPOLOS. Findings of this study enable the identification of crucial determinants and the formulation of targeted interventions to shorten the length of stay among lung cancer patients after VATS, which contribute to optimize the allocation of healthcare resources.

Introduction

The International Agency for Research on Cancer of the World Health Organization reports that the global incidence of cancer surged to 20 million new cases in 2022, with lung cancer emerging as the most prevalent malignant tumor. This disease accounted for 2.5 million new cases, representing 12.4% of all global cancer diagnoses.[1] In China alone, lung cancer cases reached an alarming figure of 870,982, making up 18% of the nation's total new cancer cases and thus becoming the most diagnosed cancer type. The high prevalence of lung cancer results in significant care and financial burden to society.[2] Among the treatment modalities, video-assisted thoracoscopic surgery (VATS) stands out as the leading therapeutic option for lung cancer, favored for its minimally invasive nature, cosmetic incisions, reduced intraoperative blood loss, and clarity of the surgical field, offering significant patient benefits. The adoption rate of VATS lobectomy exhibits considerable variation: the

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United States reporting from 30% to 40%, Italy reporting at 50%, and Denmark reporting as high as 65%.[3] Notably, VATS has been shown to diminish the length of hospital stays, lower postoperative complication rates, reduce hospitalization expenses, and decrease perioperative mortality rates.[4,5]

The duration of postoperative hospital stays serves as a crucial benchmark for evaluating patient recovery and the quality of perioperative care, reflecting the surgical team's skill, the standard of care provided, and the effective use of medical resources.[6] Observational disparities in hospital-stay lengths are attributed to differences in surgical approaches, the volume of surgeries performed, and the level of technical expertise. For instance, an analysis of data from 42 Dutch hospitals covering 6055 lung cancer surgeries revealed median lengths of stay (LOS) ranging from 3 to 8 days.[7] Similarly, in the United States, a study of 13,099 lobectomy cases reported a median LOS of 5 days, with an interquartile range (IQR) of 4–7 days.[6] A shorter LOS is indicative of quicker patient recovery, whereas a longer LOS may signal delayed recovery, higher risks of postoperative complications and mortality, and reduced long-term survival rates.[8,9] Consequently, the identification and mitigation of potential risk factors for prolonged postoperative hospital stays in lung cancer patients undergoing VATS are imperative for enhancing recovery outcomes, curtailing medical expenses, and informing clinical guidelines.

Variables such as age, gender, surgery type, surgical approach, pulmonary function indices, postoperative complications, and anesthesia duration have been recognized as risk factors for prolonged LOS among lung cancer patients.[10,11] Efforts have been made to incorporate these risk factors into comprehensive models to assess an individual patient's risk of prolonged postoperative length of stay (PPOLOS), yet such models are scarce and encounter limitations in clinical application. Hu et al. utilized logistic regression to develop a nomogram for predicting postoperative LOS in lung cancer patients after surgery, offering personalized risk assessments of PPOLOS.[10] Nevertheless, the omission of other crucial perioperative variables known to affect lung cancer postoperative LOS resulted in a receiver operating characteristic curve of less than 0.8 in both internal and external validations, highlighting a need for enhancement in its predictive capability.[10] Similarly, Jo et al. designed a predictive model for PPOLOS following cancer surgery, using machine-learning (ML) techniques on electronic health records. However, the performance of these models specifically for lung cancer was relatively low, with area under the curve (AUC) below 0.7.[12]

ML, a subset of artificial intelligence, has been instrumental in supporting the decision-making process of physicians treating cancer patients for decades.[13] Compared to traditional prediction models, ML models have strengths of flexibility, adaptability, and accuracy (ACC), thereby enhancing outcomes and interpretability.[14] MLhas been successfully applied in predicting hospital-stay durations for patients undergoing treatments such as fractures, joint replacement surgery, and intensive care, demonstrating commendable predictive ACC.[15–17] Despite these advancements, there remains a notable absence of ML models specifically designed for predicting hospital stay durations in lung cancer patients undergoing VATS.

Thus, the objective of this study is to develop precise ML models capable of predicting PPOLOS for lung cancer patients undergoing VATS, based on preoperative factors, and to evaluate the performance of these models in terms of prediction ACC and to analyze the significant features utilized within these models.

Methods

This retrospective cohort study was conducted to gather data on lung cancer patients who underwent VATS at The First Affiliated Hospital of Guangzhou Medical University between 2021 and 2022. The study received ethical approval from the Hospital Ethics Committee (IRB No. ES202307203). The requirement for informed consent was waived due to the study's retrospective design, and privacy information was anonymized when medical records were obtained.

Study population

Eligible cases included all patients who underwent VATS and were diagnosed with lung cancer at The First Affiliated Hospital of Guangzhou Medical University from January 2021 to December 2022.

Variable definition

Aligning with the precedents set in the existing literature, PPOLOS was defined as a postoperative stay exceeding the 75th percentile. In this study, a duration of $\geq$ 4 days was established as the threshold between short and prolonged hospital stays for the lung cancer cohort under investigation.

Data collection

Clinical data comprising 25 structured variables and 45 unstructured free-form textual records were retrospectively collected from medical records. Structured variables were categorized into four groups: sociodemographic information, clinical data, treatment specifics, and comorbid conditions, detailed in Table 1. The unstructured, free-form textual records from medical histories and surgical notes were summarized. Text segmentation was conducted using the jieba and spaCy libraries. This was followed by frequency analysis and manual verification by medical experts, resulting in the creation of 45 binary (0–1) textual features. These features were defined by the presence or absence of specific textual elements.

Data analysis

Statistical analysis was carried out using Pandas 1.2.4, Sklearn 0.24.1, and PyTorch 2.1.1. The ML models utilized included XGBoost, Random Forest (RF), and Neural Network, as outlined in Fig. 1. The dataset was split into an 80% training set for model development and a 20% validation set for hyperparameter tuning and performance evaluation. During the model-training phase, both structured variables and the 45 organized binary textual features were input into the three types of ML models to predict PPOLOS and develop the predictive model. The models' predictive ACC was assessed using ACC and AUC metrics. ACC measures the proportion of correctly predicted instances relative to the total sample size, indicating the model's classification ACC. An AUC value of $\geq$ 0.7 was considered indicative of strong predictive performance. The calibration plot was used to evaluate the performance on the validation dataset, whereas feature importance was determined based on feature contributions during ML training.

Table 1
Categories of study variables.

Category	Variables
Demographics	Gender, age, marital status, weight, height, smoking history
Clinical data	Alanine aminotransferase, albumin, total protein, creatinine, hemoglobin, ASA classification, NYHA class, caprini score, BADL score, hospitalization frequency
Treatment information	Length of stay, surgical duration, blood loss volume, pathological type
Comorbidities	Hypertension, ddiabetes mellitus, ccoronary heart disease, asthma, cchronic kidney disease

ASA classification, The physical status classification of the American Society of Anesthesiology; BADL, basic activities of daily living (Barthel Index); BMI, body mass index; NYHA class, New York Heart Association functional classification.

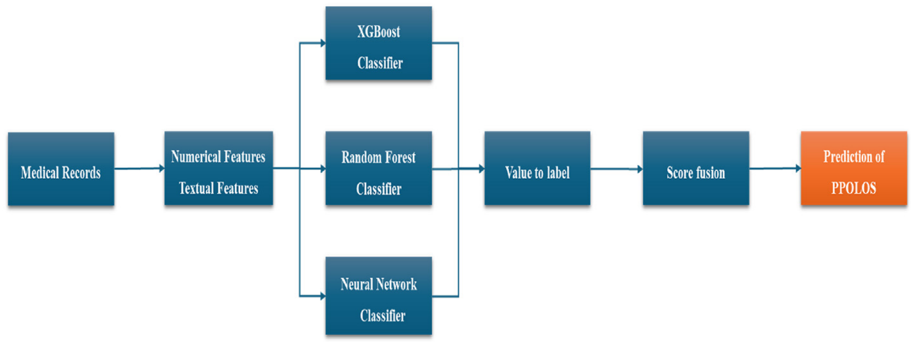

Fig. 1. Analytic schema of machine-learning algorithms. Abbreviation: PPOLOS, prolonged postoperative length of stay.

Results

Characteristics of lung cancer patients after VATS

This study included 6767 lung cancer patients, with 1481 patients (21.9%) experiencing a postoperative LOS of more than 4 days. The average age of the patients was 56.2 years, with the majority being male (4111, 60.8%). A significant proportion of the patients were married (6246, 92.3%). Adenocarcinoma was the most common diagnosis (4145, 61.3%), and the majority of patients were classified as either stage I or II according to the American Society of Anesthesiology classification (6045, 89.3%). Detailed demographic and clinical characteristics of the study participants are delineated in Table 2.

Prediction performance of the machine-learning models

Of these ML models analyzed, the RF classifier exhibited superior predictive performance, achieving an AUC of 0.792 and an ACC of 0.804. Comprehensive results are detailed in Table 3 and illustrated in Fig. 2. The calibration plot demonstrated that all three classifiers closely approximated the ideal calibration line, indicating robust calibration reliability. The performances of the three ML models on the validation set are visually represented in the calibration plot (Fig. 3).

Significance of predictive features

The relative importance of each predictive feature was assessed using the feature importance metric provided by the RF model. The five most critical features identified were surgical duration (0.116), age (0.066), creatinine (0.062), hemoglobin (0.058), and total protein (0.054). Features with an importance metric value of > 0.01 are depicted in Fig. 4, highlighting their significance in predicting PPOLOS.

Discussion

In our study, the median postoperative LOS for lung cancer patients following VATS was identified as 4 days, with 1632 patients experiencing a hospital stay exceeding this duration. This finding aligns with previous research,[10] underscoring a consistent observation across similar studies. The PPOLOS after thoracic surgery is often linked with an increase in adverse health events and a higher demand for medical resources, potentially imposing significant economic and caregiving strains on both the patients and the healthcare system. Parallel findings have been reported in other research focusing on lung cancer patients treated with VATS.[9] A retrospective analysis from national cancer database highlighted that PPOLOS is an independent prognostic marker for decreased survival post lung cancer surgery.[9] This observation was further supported by a retrospective cohort study from Canada,[18] which found a positive association between postoperative adverse events and PPOLOS in patients undergoing lung cancer resection. Similar clinical outcomes were documented in Grigor's study,[19] which also pointed out that

Table 2
Characteristics of the lung cancer patients after VATS ($N = 6767$).

Variables	Category	*n* (%)
Gender	Male	4111 (60.8)
	Female	2656 (39.2)
Marital status	Married	6246 (92.3)
	None	511 (7.7)
Smoking history	Yes	618 (9.1)
	None	6149 (90.9)
Hypertension	Yes	785 (11.6)
	None	5982 (88.4)
Diabetes mellitus	Yes	301 (4.4)
	None	6466 (95.6)
Coronary heart disease	Yes	100 (1.5)
	None	6667 (98.5)
Asthma	Yes	20 (0.3)
	None	6747 (99.7)
Chronic kidney disease	Yes	55 (0.8)
	None	6712 (99.2)
ASA classification	I–II	6045 (89.3)
	III–IV	722 (10.7)
NYHA class	I	4614 (68.2)
	II	1586 (23.4)
	III	546 (8.1)
	IV	21 (0.3)
Hospitalization frequency	0	4323 (63.9)
	1	1043 (15.4)
	2	1317 (19.5)
	≥ 3	84 (1.2)
Pathology Subtypes	Adenocarcinoma	4145 (61.3)
	Squamous cell carcinoma	649 (9.6)
	Others	1973 (29.2)
Age (years), mean (SD)		56.2 (12.6)
Weight (kg), mean (SD)		60.9 (11.4)
Height (cm), mean (SD)		163.1 (7.8)
BMI (kg/cm^2), mean (SD)		22.8 (3.7)
Blood loss (ml), mean (SD)		34.0 (168.7)
Total protein (g/L), mean (SD)		72.1 (6.3)
Creatinine (mg/dL), mean (SD)		83.2 (44.1)
Albumin (g/L), mean (SD)		40.8 (3.9)
Hemoglobin (g/L), mean (SD)		130.2 (17.3)
Alanine aminotransferase (u/L), mean (SD)		24.3 (40.4)
Surgical duration (day), mean (SD)		101.7 (50.3)
Tumor size (mm), mean (SD)		4.6 (14)
Caprini score, mean (SD)		2.8 (2.6)
BADL score, mean (SD)		98.8 (7.0)

ASA classification, The physical status classification of the American Society of Anesthesiology; BADL, basic activities of daily living (Barthel Index); BMI, Body mass index; NYHA class, New York Heart Association functional classification; SD, standard deviation; VATS, video-assisted thoracoscopic surgery.

Table 3
Performance of three machine learning models.

Model	Accuracy	AUC	Precision	Recall	F1
Random forest classifier	0.804	0.792	0.739	0.604	0.620
XGB classifier	0.799	0.779	0.709	0.631	0.649
NN classifier	0.774	0.722	0.540	0.527	0.479

AUC, area under the curve; NN, Neural Network.

patients encountering PPOLOS reported a significant decline in their postoperative experience, potentially diminishing the quality of care provided.

Moreover, minimizing extended hospital stays is anticipated to not only liberate bed capacity and healthcare staff's time but also to reduce the financial burden associated with extended patient hospitalization, thereby improving healthcare quality and fostering sustainable healthcare development.[20] Consequently, it becomes essential for healthcare practitioners to implement a systematic framework for the comprehensive assessment of lung cancer patients. This strategy aims to identify those at a heightened risk for PPOLOS and their associated risk factors, enabling proactive management. Such an approach is designed to enhance bed utilization, optimize care delivery, and achieve cost efficiency, contributing to the improvement of patient outcomes and the overall efficiency of the healthcare system.

Predictive models for PPOLOS in lung cancer patients following VATS are notably limited. This study primarily aims to validate the efficacy of ML technologies in forecasting PPOLOS. Our findings indicate that ML models, particularly those utilizing RF, XGBoost, and Neural Networks, exhibit strong predictive performance for PPOLOS, with the AUC values ranging between 0.722 and 0.792, and prediction accuracies spanning from 0.774 to 0.804. These results position our study as a significant contribution to the field, surpassing previous investigations that have attempted to develop predictive models for PPOLOS in lung cancer VATS patients. Earlier research using ML for PPOLOS prediction has reported similar or less favorable outcomes,[10,12] a discrepancy that can likely be attributed to the larger sample size and the richer data characteristics encompassed in the current study.

Selecting the appropriate analytical methods of ML is paramount and must be tailored to the characteristics of the research data, including the type and volume of data, as well as the distribution of samples. Our study's dataset comprised both numerical and textual data, characterized by a significant volume and variability in the number of features and sample distribution. Consequently, we deployed three analytical models: RF, XGBoost, and Neural Networks. When considering both AUC and ACC, the RF model emerged as the most capable predictor, boasting an AUC of 0.792 and an ACC of 0.804. XGBoost followed closely with an AUC of 0.779 and an ACC of 0.799, whereas the Neural Network model

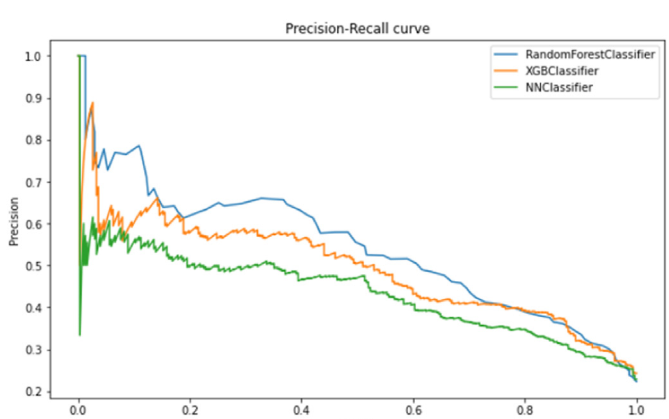

Fig. 2. Precision–recall curves of the three models in the validation set.

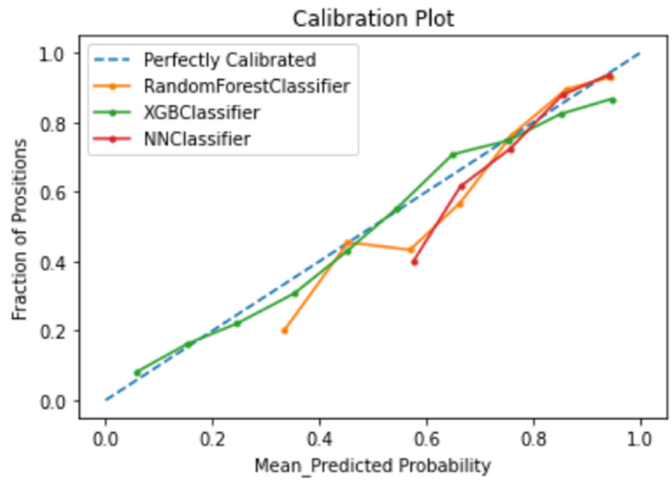

Fig. 3. Calibration plots of the three ML models in the validation set. ML, machine-learning.

showed the least predictive power, with an AUC of 0.722 and an ACC of 0.774.

The dataset exhibited high dimensionality and imbalance, conditions under which the RF model, leveraging decision trees as base classifiers, excels. By using voting or averaging to mitigate the influence of individual decision trees, this model demonstrates reduced sensitivity to outliers and minimizes the risk of overfitting through the random selection of feature and sample subsets for training. These qualities significantly contribute to the RF model's superior predictive performance.[21] Thus, using ML, and specifically the RF approach, for predicting postoperative outcomes based on patient characteristics facilitates early identification of PPOLOS. This early detection is instrumental in optimizing medical resource allocation and refining treatment protocols, thereby enhancing patient outcomes.

Evaluating the significance of predictive variables was another aim of this research. The RF model identified the five most critical variables for PPOLOS prediction: surgical duration, age, creatinine, hemoglobin, and total protein. These findings underscore the potential of targeted interventions and adjustments in preoperative and postoperative care strategies to mitigate the risk of prolonged hospital stays, thereby improving the efficiency and effectiveness of lung cancer patient management.

Although the specific impact of surgical duration on the postoperative LOS for lung cancer patients undergoing VATS remains largely unknown, a longer operation time has been consistently associated with an extended LOS across various cancer surgeries, including colorectal,[22] endometrial,[23] arthroplasty,[24] and spinal deformity surgery.[25] Moreover, extended surgical times are linked to an array of postoperative complications such as surgical site infections,[26] pneumonia, atelectasis, reintubation, and unexpected admissions to intensive care units,[27,28] all of which contribute to a PPOLOS.[29]

Anemia, widely recognized for its prevalence and prognostic significance in cancer patients,[30] has been further corroborated by recent investigations as a determinant of hospital-stay length. A multicenter analysis indicated that patients undergoing noncardiac and nonobstetric surgeries with preoperative anemia experienced markedly longer hospitalizations.[31] Similarly, research by Sanoufa et al. identified preoperative anemia as a significant predictor of extended hospital stays among patients receiving spinal surgery,[32] a finding echoed in the context of cancer patient care.[33] Despite these associations, the underlying mechanisms that connect anemia with LOS in surgical cohorts remain unclear, necessitating additional research to devise effective interventions aimed at optimizing perioperative management for affected individuals.

Age has been validated as a significant factor influencing PPOLOS in several studies.[34,35] Notably, Hu et al.[10] highlighted that the length of

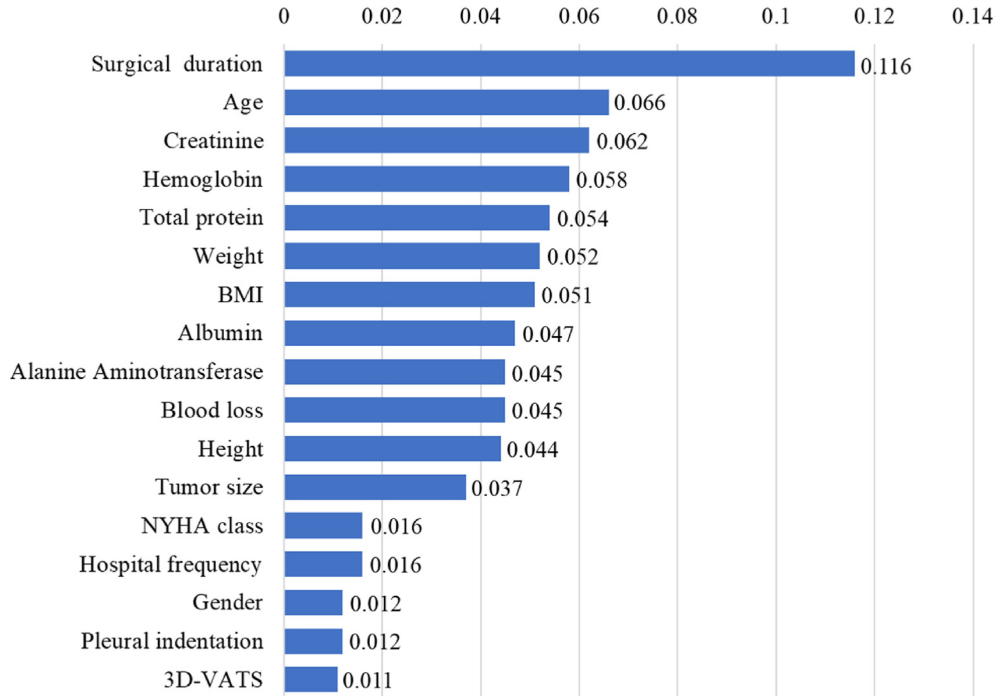

Fig. 4. Importance of the predicting variables. BMI, body mass index; BADL, basic activities of daily living (Barthel Index); NYHA class, New York Heart Association functional classification; 3D-VATS, 3-dimensional video-assisted thoracoscopic surgery.

hospital stay begins to incrementally increase for patients aged over 50, with a more pronounced surge in LOS observed beyond the age of 70. These insights underscore the complexity of predicting PPOLOS and the necessity of incorporating a broad spectrum of patient characteristics and clinical variables into predictive models to enhance the ACC and relevance of such assessments in the clinical setting.

Total protein and creatinine have been identified as significant predictive factors for PPOLOS in lung cancer patients, a novel finding given the current scarcity of research on their predictive value in this context. Both creatinine and total protein are critical markers for assessing nutritional status,[36,37] with malnutrition known to be associated with increased mortality, compromised functional status, and extended hospital stays.[38–40] Consequently, the significance of preoperative nutritional management for lung cancer patients is increasingly recognized by oncology specialists as a means to enhance postoperative recovery and mitigate complications.[41] Moreover, our research highlighted additional pivotal features, including albumin, body mass index, alanine aminotransferase, and blood loss, among others, offering a more holistic preoperative assessment tool.

This study has several strengths: (1) It features a robust sample size enriched with diverse data characteristics. (2) Variables for model construction were obtained from hospital records, streamlining data collection and supporting timely clinical decision-making for healthcare providers. (3) The developed model demonstrates high predictive ACC, lending credibility to the findings. Nonetheless, this study has following limitations: (1) The data were collected from a single medical center, which may affect the broader applicability of the results. (2) The retrospective nature of data extraction from medical records could overlook other potentially significant predictors for PPOLOS. (3) Focusing exclusively on particular subsets of lung cancer surgery may restrict the applicability of our conclusions. To gain a more comprehensive understanding of the postoperative prognosis for lung cancer patients, future research should use a broader approach. This could include a prospective multicenter study design, the incorporation of additional data sources more relevant to patient outcomes, and the development of models using a combination of multiple ML algorithms.

Conclusions

This study developed and evaluated three ML models for predicting PPOLOS in lung cancer patients undergoing VATS. The findings revealed that the RF model is most accurately predicting the PPOLOS. These ML models will be integrated more effectively into clinical practice when they are incorporated into healthcare information systems. This integration will facilitate the identification of risk features' effects and the development of personalized perioperative interventions, which aim to reduce the length of hospital stays for lung cancer patients after VATS, ultimately lowering costs for both patients and healthcare systems.

Ethics statement

The study received ethical approval from the Hospital Ethics Committee (IRB No. ES202307203).

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CRediT authorship contribution statement

All authors have reviewed and approved the manuscript. GZ collected the data, GZ and XL drafted the manuscript as co-first authors. YH and QL conducted data analysis. XH and YZ participated in the conceptualization and methodology of the study. GZ and LR contributed to data collection and data discussions. HX and YZ conducted the manuscript review and editing as the corresponding author. All authors had full access to all the data in the study, and the corresponding author had final responsibility for the decision to submit for publication. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

Declaration of competing interest

The authors declare no conflict of interest. The corresponding author, Dr. Yingchun Zeng, serves as a member of the editorial board of the *Asia-Pacific Journal of Oncology Nursing*. The article has undergone the journal's standard publication procedures.

Data availability statement

The data sets generated during this study are available from the corresponding author on reasonable request.

Declaration of Generative AI and AI-assisted technologies in the writing process

No AI tools/services were used during the preparation of this work.

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