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Construction of a machine learning-based prediction model for intraoperative acquired pressure injury in children undergoing neurosurgery

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Abstract

Background: Intraoperative acquired pressure injury (IAP) is a common complication in children undergoing neurosurgery, and early identification of its risk factors is essential. However, the risk factors for IAP in this population are not well understood, and no study has reported a machine learning-based prediction model. This study aimed to construct and validate a prediction model for IAP in children undergoing neurosurgery and to provide a reference for IAP prevention.

Methods: The clinical data of 776 children who underwent neurosurgery in a tertiary children's hospital in Chongqing from January to June 2023 were retrospectively collected. Variables were screened using least absolute shrinkage and selection operator (LASSO) regression. Nine machine learning algorithms were selected, and the models were constructed and validated using ten-fold cross-validation and a validation set. The predictive effects of each model were compared using receiver operating characteristic (ROC) curves, cross-validation results, and efficiency metrics, to construct the optimal model for predicting IAP in children undergoing neurosurgery. Finally, the SHapley Additive exPlanations (SHAP) toolkit was used to explain and analyze the model and to identify the most important factors causing IAP.

Results: The incidence of IAP in children undergoing neurosurgery was 7.9%. The extreme gradient boosting (XGBoost) model had the best predictive performance, with sensitivity, specificity, precision, F1 score, and area under the ROC curve (AUC) of 0.8889, 0.4813, 0.126, 0.2207, and 0.7325, respectively. The decision curve showed that the predicted probability of IAP occurrence by this model was consistent with the actual probability. Through visualization analysis of the SHAP swarm plot, clinical indicators such as intraoperative blood loss, surgical position, patient age, operation duration, anesthesia duration, and use of external force were identified as key risk factors.

Conclusions: The prediction model for neurosurgical children constructed in this study has certain predictive efficacy and can provide a scientific basis for clinical nurses to identify high-risk children with IAP early and to take personalized preventive measures.

Keywords: Neurosurgery; Intraoperative acquired pressure injury; Machine learning; Children; Prediction model

1 Introduction

Pediatric neurosurgical procedures are mostly delicate and complex operative surgeries that are time-consuming, and children usually need to assume various forced positions during surgery to facilitate the procedure. Meanwhile, the use of intraoperative instruments such as drills and milling cutters leads to combined local tissue compression; moreover, children are mostly confined to bed rest in the early postoperative period, all of which increase the risk of intraoperative acquired pressure injury¹ (IAPI). A study² showed that the incidence of IAPI in neurosurgical children was 11.5%. IAPI not only causes obvious discomfort to children, but may also lead to prolonged hospital stay, increased nursing costs, and even infection, thereby endangering life³. Therefore, early identification of risk factors for IAPI in neurosurgical children and efficient and accurate risk prediction before surgery are essential. In recent years, data mining techniques have advanced and become a strategy for constructing risk assessment models. Previously, we established a nomogram prediction model for IAPI in neurosurgical children through data mining⁴ and found it had a moderate predictive effect (c-index = 0.79). Machine learning is another data mining method that can automatically capture potential associations among multidimensional variables, identify individual characteristics more accurately, and improve the accuracy and reliability of IAPI risk prediction. To date, no study has reported the use of machine learning to construct a prediction model for IAPI in neurosurgical children. Therefore, based on multiple machine learning algorithms, this study constructed an IAPI risk prediction model for neurosurgical children again and compared it with the previous nomogram model, aiming to screen out the optimal model through comparison of multiple algorithms and to provide a reference for healthcare professionals to accurately identify high-risk children early and formulate targeted interventions.

2 Subjects and tools

2.1 Study subjects

This was a retrospective study using convenience sampling to select children who underwent neurosurgery in a tertiary children's specialized hospital in Chongqing from January to June 2023 as the study subjects. Inclusion criteria: age ≤ 18 years; undergoing surgical treatment and survival. Exclusion criteria: pre-existing pressure injury; skin diseases affecting skin observation; non-pressure injuries such as adhesive tape stripping injuries; and missing data. The study was approved by the Institutional Review Board of Children's Hospital of Chongqing Medical University (approval number: (2022) Ethical Review (Research) No. 586).

Given that the outcome of this study was a binary variable, the sample size for the clinical prediction model was calculated using the 10 events per variable (EPV) principle⁹, i.e., at least 10 samples (10 EPV) are required per variable for model development. In the development cohort dataset,

the effective sample size is determined by the total number of study variables. Referring to previous literature ², the incidence of pressure injury in neurosurgical children is approximately 11%. This study included 14 risk factors for IAPI in neurosurgical children. Considering that approximately 10% of samples might be invalid, the required total sample size was calculated as: $14 \times 5 \div 11\% \times (1 + 10\%) \approx 700$. A total of 776 children were included, which met the sample size requirement.

2.2 Research tools

2.2.1 IAPI diagnostic criteria

The diagnostic criteria for IAPI adopted the 2019 standards established by the National Pressure Ulcer Advisory Panel (NPUAP), which are classified into stage I, II, III, IV, unstageable, and deep tissue injury.

2.2.2 Data collection instruments and methods

A self-designed general information questionnaire for neurosurgical children was used for data collection, including a general information questionnaire and preoperative and intraoperative risk factor questionnaires, see attachment 1 for details. The general information questionnaire included patient ID, admission number, diagnosis, date of birth, height, weight, and gender. The preoperative risk factor questionnaire specifically included the last preoperative hemoglobin, the last preoperative hematocrit (HCT), body mass index (BMI), and the Braden Q score upon entering the operating room. The intraoperative risk factor questionnaire included the American Society of Anesthesiologists (ASA) classification ⁵ based on the patient's physical condition and surgical risk before anesthesia, operation time, anesthesia time, surgical position, intraoperative hypothermia, surgical type (elective or emergency), intraoperative blood loss, and IAPI occurrence.

BMI was calculated as weight divided by the square of height. Preoperative laboratory results such as hemoglobin and hematocrit were based on the last preoperative measurement. Intraoperative temperature was automatically collected every 5 minutes through the anesthesia information system; intraoperative hypothermia was defined as temperature <36 °C maintained for >30 minutes. Surgical position was classified as supine, lateral, or prone. IAPI in neurosurgical children was collected from records assessed and documented by ward nurses, operating room nurses, and recovery room nurses before and after surgery and during transfer.

2.2.3 Quality control

This study implemented strict quality control in planning, implementation, and data collection, with unified training for the data collection process. To ensure the completeness and accuracy of the data of all included subjects, data were entered by a designated person and verified one by one by the researchers to avoid input errors.

3 Methods

3.1 Statistical analysis

SPSS 25.0 was used for statistical analysis. Continuous variables were described as mean $\pm$ SD, and categorical variables as frequencies and percentages. In the analysis of risk factors for IAPI in children undergoing neurosurgery, the Kolmogorov–Smirnov (K-S) test was used to assess the normality of continuous variables; normally distributed variables were compared using the independent samples t-test, and non-normally distributed variables using the rank-sum test. For categorical variables among the risk factors, the χ^2 test was used to compare the IAPI and non-IAPI groups. A significance level of $P < 0.05$ was considered statistically significant.

3.2 Overview of machine learning algorithms

Analysis was performed using R (version 4.3.3). The data were randomly divided into a training set and a validation set at a ratio of 70%:30%. Nine machine learning algorithms were used to construct the IAPI risk prediction model for neurosurgical children: logistic regression (LR), random forest (RF), neural network (NNET), extreme gradient boosting (XGBoost), gradient boosting machine (GBM), support vector machine (SVM), naive Bayes (NB), K-nearest neighbors (KNN), and decision tree (DT). To further optimize model performance, ten-fold cross-validation and grid search were used to tune parameters on the training set. Finally, the validation set was used for validation to evaluate the predictive ability of the model. The detailed process is shown in Fig. 1.

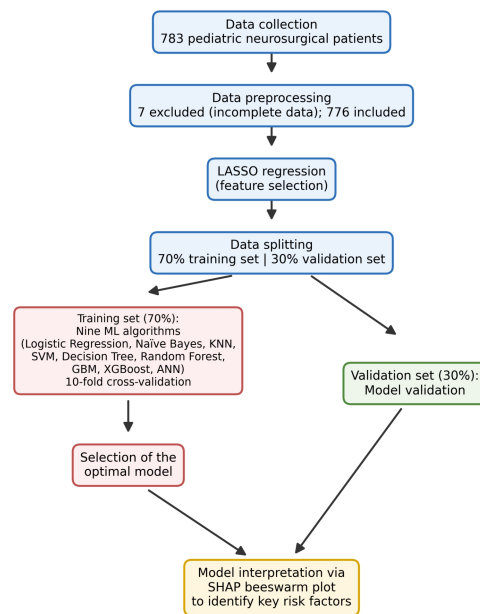


Figure 1. Schematic diagram of a machine learning–based risk prediction model for intraoperative pressure injury in children.

3.2.1 Feature selection

This study selected LASSO regression⁶ as the feature selection method. LASSO is a data dimensionality reduction method that can be used to select predictors associated with the primary

outcome. According to the tuning parameter λ , it shrinks the coefficients of many irrelevant features to zero and uses the retained features with non-zero coefficients for regression model fitting, thereby achieving variable screening.

3.2.2 Model evaluation metrics

This study used the AUC, precision, sensitivity, specificity, and balanced F-score (F1) as the main model performance evaluation metrics ⁷. Decision curve analysis (DCA) was used to evaluate the clinical utility of the prediction model. For the optimal prediction model identified by performance comparison, this study used the SHAP tool ⁸ for interpretability analysis, to determine the importance of each feature (predictor) in the model's decision process and to visually explain the decision role of features in the model.

4 Results

4.1 IAPI occurrence and baseline characteristics

This study collected data from 783 children undergoing neurosurgery, and 7 were excluded due to incomplete information, leaving 776 children for final analysis. Among them, 488 (62.89%) were male and 288 (37.11%) were female. Based on previous literature and feature engineering, the included factors were stratified; the basic information is shown in Table 1.

The original data were randomly divided into a training set and a validation set at a ratio of 70%:30%, with 544 in the training set and 232 in the validation set. The model was constructed using the training set, and internal validation of the training set model was performed through ten-fold cross-validation. The optimal model obtained from cross-validation was further validated using the validation set, and the predicted results were compared with the actual results of the validation set to test the model performance.

The incidence of IAPI in neurosurgical children was 7.9% (62/776). Among the 62 children with IAPI, stage I accounted for 59 cases (95.16%), stage II for 2 cases (3.22%), and stage III for 1 case (1.61%); a total of 90 IAPI sites occurred, of which 14 children had two different sites, 4 had three different sites, and 2 had four different sites, while the remaining 42 children had one site. Among the IAPI sites, the cheek was the most frequent (30.00%), followed by the forehead (16.67%) and temple (11.11%); the distribution is shown in Table 2.

Table 1 Baseline characteristics of enrolled children (n = 776)

Variable	Total (n=776)	IAPI (n=62)	Non-IAPI (n=714)	Statistic	P
Age (months)					
<12	129	20	109	-3.621	<0.001
12–36	131	13	118	-3.621	<0.001
>36	516	29	487	-3.621	

Sex					
Female	288	27	261	1.196	0.274
Male	488	35	453	1.196	0.274
BMI					
<17.90	588	49	539	0.390	0.532
≥17.90	188	13	175	0.390	0.532
Braden Q score					
≤16	305	31	274	3.231	0.072
>16	471	31	440	3.231	0.072
Preoperative hemoglobin (g/L)					
<118	486	45	441	2.851	0.091
≥118	290	17	273	2.851	0.091
Preoperative hematocrit (%)					
<35	410	43	367	7.379	0.007
≥35	366	19	347	7.379	0.007
Intraoperative blood loss (mL)					
<10	501	20	481	-5.128	<0.001
10–100	148	25	123	-5.128	<0.001
>100	127	17	110	-5.128	<0.001
Lowest intraoperative temperature (°C)					
<36	487	42	445	0.716	0.397
≥36	289	20	269	0.716	0.397
Anesthesia time (h)					
<3	399	25	374	3.321	0.068
≥3	377	37	340	3.321	0.068
Surgical position					
Supine	560	33	527	18.102	<0.001
Lateral	80	6	74	18.102	<0.001
Prone	136	23	113	18.102	<0.001
Use of power drills/milling cutters					
No	185	3	182	13.400	<0.001

Yes	591	59	532	13.400	<0.001
ASA classification					
II	285	26	259	-0.921	0.357
III	444	33	411	-0.921	0.357
IV	47	3	44	-0.921	0.357
Operation time (h)					
<2	509	26	483	-3.772	<0.001
2–4	138	21	117	-3.772	<0.001
>4	129	15	114	-3.772	<0.001
Surgical type					
Emergency	273	19	254	0.608	0.436
Elective	503	43	460	0.608	0.436

Table 2 Distribution of IAPI sites (n = 62)

Site	Stage I	Stage II	Stage III or above	Total	Proportion
Cheek	27			27	30.00%
Forehead	15			15	16.67%
Temple	7	2	1	10	11.11%
Chest wall	8			8	8.89%
Eye	7			7	7.78%
Finger	5			5	5.56%
Knee	4			4	4.44%
Sacrococcygeal	3			3	3.33%
Ear	3			3	3.33%
Anterior superior iliac spine	3			3	3.33%
Occiput	2			2	2.22%
Heel	2			2	2.22%
Toe	1			1	1.11%

4.2 Construction of the prediction model

4.2.1 Feature selection results

Figure 2 shows the results of variable screening by LASSO regression. Panel A shows the relationship between $\log(\lambda)$ and AUC; as the tuning parameter increases, the number of variables with non-zero coefficients decreases and the AUC generally shows a downward trend. Panel B shows the vertical dashed line representing the optimal tuning coefficient ($\log \lambda$) corresponding to the maximum

AUC. Through LASSO regression, 13 features with non-zero coefficients were finally selected when the AUC was maximized: age, sex, Braden Q score, preoperative hemoglobin, preoperative hematocrit, intraoperative blood loss, operation time, anesthesia time, surgical position, use of drills and milling cutters and other instruments increasing external force, ASA classification, surgical type, and BMI.

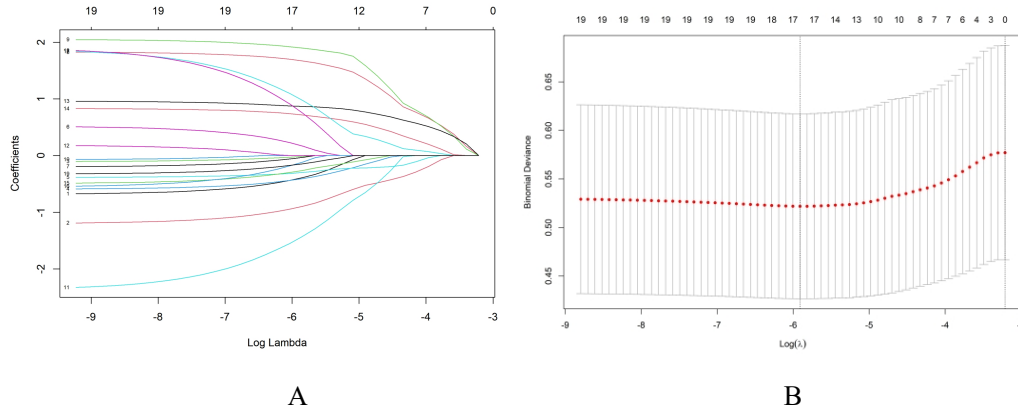


Figure 2. A. Coefficient path plot of the LASSO regression; B. Ten-fold cross-validation plot for selecting the optimal regularization parameter (λ).

4.2.2 Training and validation results

4.2.2.1 Comparison of AUC

The nine constructed models were compared using ROC curves. By comparing the AUC of each model, the XGBoost model performed relatively stably in both the ten-fold cross-validation on the training set (Fig. 3) and the validation set (Fig. 4), with AUC values of 0.7380 and 0.7325, respectively.

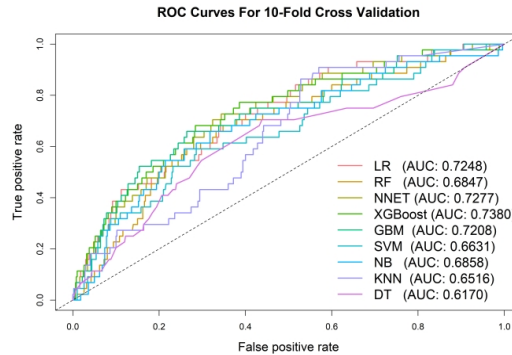


Figure 3. ROC curve of the predictive performance in the training set using 10-fold cross-validation

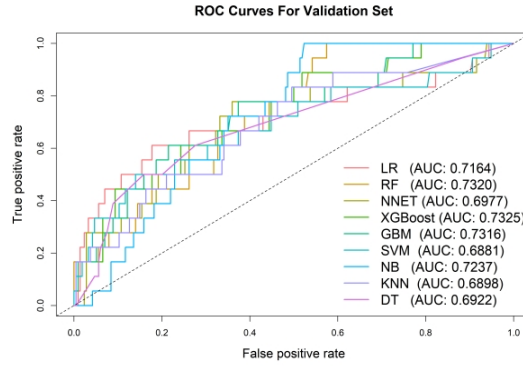


Figure 4. ROC curve of the model's predictive performance in the validation set

4.2.2.2 Overall comparison under default parameters

Under default parameters, the comprehensive comparison of the nine models across sensitivity, specificity, precision, and F1 showed that in the ten-fold cross-validation on the training set, the sensitivity of XGBoost was slightly lower than that of KNN, NNET, and DT; however, in the validation set XGBoost maintained good sensitivity (0.8889) and stable predictive performance compared with the other models. The detailed performance of all nine models in the training set and validation set is presented in Tables 3 and 4.

Table 3 Performance of the nine models in the training set

Model	AUC	Sensitivity	Specificity	Precision	F1
LR	0.7248	0.6818	0.658	0.1493	0.2449
RF	0.6847	0.6818	0.652	0.1471	0.2419
NNET	0.7277	0.7273	0.656	0.1569	0.2581
XGBoost	0.7380	0.6818	0.716	0.1744	0.2778
GBM	0.7208	0.6591	0.736	0.1801	0.2829
SVM	0.6631	0.5909	0.714	0.1538	0.2441
NB	0.6858	0.6591	0.682	0.1543	0.2500
KNN	0.6516	0.9091	0.430	0.1231	0.2168
DT	0.6170	0.7045	0.562	0.1240	0.2109

Table 4 Performance of the nine models in the validation set

Model	AUC	Sensitivity	Specificity	Precision	F1
LR	0.7164	0.6111	0.8224	0.2245	0.3284
RF	0.7320	1.0000	0.4252	0.1277	0.2264
NNET	0.6977	0.7778	0.6402	0.1538	0.2569
XGBoost	0.7325	0.8889	0.4813	0.1260	0.2207
GBM	0.7316	0.7778	0.6262	0.1489	0.2500
SVM	0.6881	0.5000	0.8598	0.2308	0.3158
NB	0.7237	1.0000	0.4766	0.1385	0.2432
KNN	0.6898	0.8333	0.5047	0.1240	0.2158

DT	0.6922	0.5000	0.8411	0.2093	0.2951
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4.2.2.3 Decision curve analysis

Calibration analysis was performed for the constructed models. In the training set, the NNET and decision tree models had the best net benefit; in the validation set, XGBoost showed greater net benefit than the other models, indicating that XGBoost is the optimal model with good clinical applicability (Fig. 5).

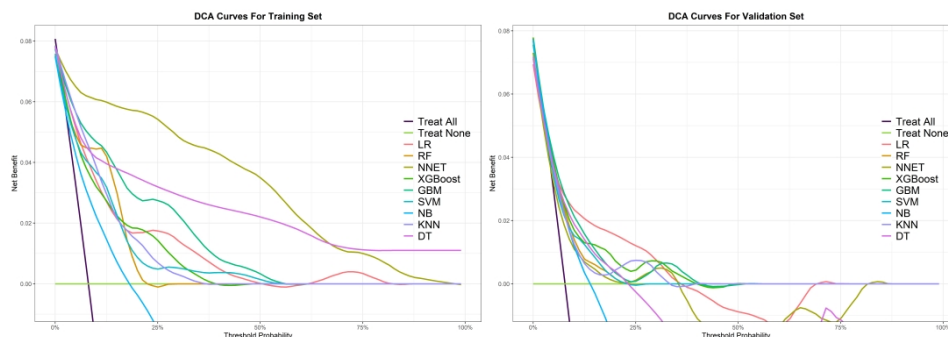


Figure 5. Clinical decision curve analysis in the training and validation set

4.2.3 Risk factor analysis

To visually reveal the importance of predictors to the model prediction results, this study used the SHAP swarm plot to visualize the feature importance of the optimal model (XGBoost). The top six most important risk factors were intraoperative blood loss, surgical position, age, anesthesia time, operation time, and use of external force (Fig. 6).

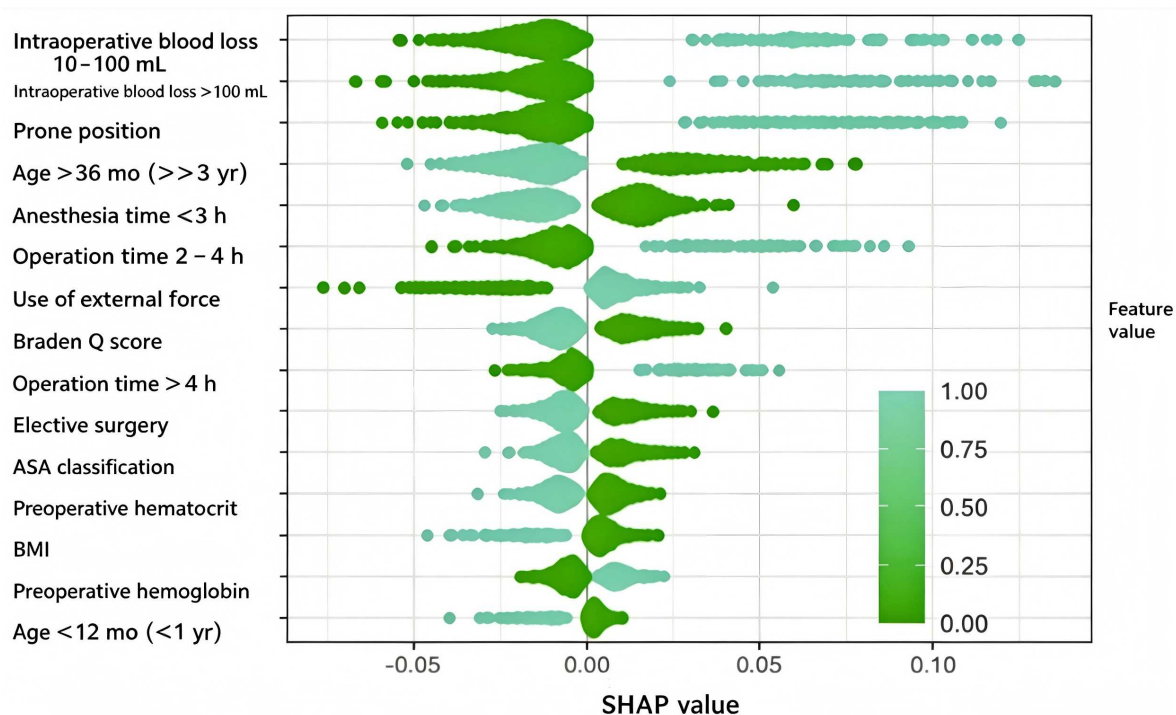


Figure 6. Feature importance scores of the Extreme Gradient Boosting (XGBoost) model for predicting IAPI in pediatric neurosurgical patients.

5 Discussion

5.1 Occurrence of IAPI in neurosurgical children

The results of this study showed that the incidence of IAPI in neurosurgical children was 7.9%. This may be because, under the anesthetic state, neurosurgical children have relatively complex conditions and poor internal environment stability, making them a high-risk population for IAPI⁹. Our result was lower than that reported in previous foreign studies, which may be due to differences in region, race, and operation duration.

This study found that the occurrence of IAPI in neurosurgical children was most frequent on the face, followed by the forehead and temple, which is similar to the results of related studies¹⁰. The reason may be related to the fact that neurosurgical procedures are mostly concentrated in the head and face: during surgery, the head and face are subjected to additional pressure from arm placement and retractor use, thereby increasing the risk of IAPI at these sites¹¹.

In addition, the pressure injuries collected in this study were mainly stage I, which is consistent with related studies¹². However, some studies¹³ have pointed out that stage I pressure injury is a potential risk factor for more severe injury, and if not taken seriously it may progress to deeper injury. Therefore, medical staff should pay attention to stage I pressure injury and actively take preventive measures to avoid the occurrence of more severe intraoperative acquired pressure injury.

5.2 Analysis of the machine learning-based prediction model

5.2.1 Construction of the prediction model

In previous studies^{14,15}, the most common method for constructing machine learning prediction models was to identify their subtle differences by comparing multiple models. This study adopted a similar idea: nine algorithms were selected, namely logistic regression, naive Bayes, K-nearest neighbors, support vector machine, decision tree, random forest, gradient boosting machine, extreme gradient boosting, and artificial neural network, to explore and construct a risk prediction model suitable for IAPI in neurosurgical children. The selected algorithms cover linear models, tree models, ensemble learning, and other methods.

During model construction, ten-fold cross-validation was first performed on the training set, and then validation was performed on the validation set to ensure the stability and generalizability of the model. Compared with the constructed nomogram prediction model, the machine learning-based model in this study additionally identified "operation time" as an important risk factor for IAPI in neurosurgical children; at the same time, the study performed interpretability analysis on the optimal model with the best predictive performance and clarified the importance of each feature in the model.

5.2.2 Performance evaluation of the XGBoost model

This study found that the AUC of the XGBoost ROC curve was 0.733, which has certain discrimination, practicality, and calibration for the prediction of IAPI in neurosurgical children, and is consistent with the results of Nakagami et al.¹⁶ XGBoost¹⁷ is based on the gradient boosting framework, which constructs multiple decision trees and uses the gradient boosting strategy to optimize errors, effectively handling the nonlinear relationships and complex interactions in the data that are difficult to capture in traditional models; in addition, XGBoost also has a strong ability to handle multicollinearity among variables, and performs well in the processing of missing values and outliers, which is of great significance for processing clinical data with unmeasured indicators. However, compared with the previous nomogram model, the AUC of this study (0.79) was slightly lower, and the sensitivity was higher than that of the nomogram model, which also indicates to a certain extent the potential of integrating artificial intelligence in the development of IAPI risk prediction models. Although some studies^{18,19} have shown that the average AUC of machine learning-based models is higher than that of traditional models, its effectiveness needs further verification in practical application.

5.2.3 Interpretability analysis

In the process of constructing the prediction model, feature importance analysis is a key link, which can quantify the contribution of each variable to the prediction result and prioritize it. However, traditional methods have limitations in explaining the mechanism of feature influence and can hardly clarify the relationship between variables and prediction results. In this research context, the SHAP swarm plot can visualize the decision basis of the model and effectively improve the decision transparency of the machine learning model²⁰. Especially in the field of pressure injury risk assessment, a highly transparent prediction model can help nurses intuitively understand the logical process of risk prediction, clarify the decision basis for risk grading, and thereby enhance the trust and adoption willingness of clinical workers toward the prediction results.

Through visualization analysis of the SHAP swarm plot, this study found that intraoperative blood loss, surgical position, age, operation time, anesthesia duration, and use of external force were important risk factors for IAPI in neurosurgical children. Multiple studies^{21–23} have shown that operation time, age, and prone position are important risk factors for pediatric IAPI, which is consistent with the results of this study. The analysis of the reasons is as follows: pressure injury is skin damage caused by the interaction of pressure, friction, and shear force. When the prone position is adopted during surgery, the reduced contact area increases friction, venous return decreases, and inferior vena cava compression reduces tissue perfusion; when skin pressure exceeds capillary pressure (12–32 mmHg, 1 mmHg = 0.133 kPa), tissue ischemia occurs, which can cause tissue damage after a certain time. Younger children have thinner epidermis and immature dermal capillary network, resulting in lower skin resistance to pressure and shear force, and thus are prone to IAPI. This study shows that intraoperative blood loss is an important risk factor for IAPI in neurosurgical children, which is consistent with the results of Qu et al.²⁴. The analysis of the reasons is that with the increase of intraoperative blood loss, arterial blood supply

becomes abnormal, and then tissue reflux perfusion is poor and hypoxia occurs, which reduces skin resistance and increases the risk of IAPI. In addition, this study also found that anesthesia duration is an important risk factor for neurosurgical children, which is consistent with the results of foreign scholars ²⁵. All children in this study received general anesthesia. Due to the complex mechanism of anesthesia ²⁶, the body experiences dilation of resistance and capacitance vessels, insufficient microcirculation perfusion, decreased cellular oxygen consumption rate, and prolonged microcirculation perfusion recovery time, which exacerbates the risk of IAPI in perioperative neurosurgical children. Finally, this study found that the use of instruments such as drills and milling cutters that increase external force raises the risk of IAPI in neurosurgical children, which is consistent with the results of domestic scholars ²⁷. The analysis of the reasons may be that neurosurgical children often need to use various power drills during surgery, and the oscillating friction increases with the power drill, which easily damages the stratum corneum when acting on the skin, thereby exacerbating the risk of IAPI.

In summary, in the process of constructing the IAPI prediction model for neurosurgical children, this study first clarified the relevant factors of intraoperative pressure injury in neurosurgical children, which helps model training and improves the accuracy of IAPI prediction in neurosurgical children; secondly, this study compared the predictive performance of nine machine learning risk prediction models through ten-fold cross-validation and validated them in the validation set, and the modeling process was complete. The final results showed that the XGBoost model performed well; finally, this study identified the important risk factors (intraoperative blood loss, prone position, age, operation time, anesthesia time, and use of external force) causing IAPI in neurosurgical children through the SHAP swarm plot. Operating room nurses can use this swarm plot to omit some scale assessment steps in the IAPI assessment process of neurosurgical children, timely screen out children at high risk of IAPI, help reduce assessment time, and improve the accuracy of prediction.

6 Conclusion

The prediction model for neurosurgical children constructed in this study has certain predictive efficacy and can provide a scientific basis for clinical nurses to identify high-risk children with IAPI early and to take personalized preventive measures.

7 Limitations

This study has two main limitations. First, in the process of model construction, the selection of relevant risk factors is crucial because it directly affects the accuracy of feature extraction and output results of the machine learning model. Although this study considered many risk factors related to the occurrence of IAPI in neurosurgical children during model construction, the development and validation of this model both used retrospective data, so some potential risk factors may have been ignored. In particular, the age problem also has the phenomenon of excessive age span and unbalanced distribution.

Future studies could consider introducing more risk factors related to IAPI and exploring children at different age stages to further optimize and upgrade the model.

Second, in the process of model construction, this study preliminarily explored the interaction among the various risk factors and excluded the interaction among the influencing factors during model construction. However, the prediction model constructed in this study has not been externally validated. Future studies could continue to explore the interaction of various risk factors on this basis to optimize the model.

List of abbreviations

ASA: American Society of Anesthesiologists; AUC: area under the receiver operating characteristic curve; BMI: body mass index; DCA: decision curve analysis; EPV: events per variable; HCT: hematocrit; IAPI: intraoperative acquired pressure injury; LASSO: least absolute shrinkage and selection operator; NPUAP: National Pressure Ulcer Advisory Panel; SHAP: SHapley Additive exPlanations; XGBoost: extreme gradient boosting.

Declarations

Ethics approval and consent to participate

This retrospective study was approved by the Hospital Ethics Committee (No. (2022) Ethical Review (Research) No. 586). Because the study used anonymously collected retrospective data, the requirement for informed consent was waived by the Ethics Committee.

Consent for publication

Not applicable.

Availability of data and materials

The data are confidential and will not be disclosed; scholars who wish to access the data may contact the corresponding author.

Competing interests

All authors declare that they have no competing interests.

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Authors' contributions

HAN Shanshan: conceptualization and design, data collection, data curation and analysis, model construction, manuscript writing. ZHONG Qian and LIU Xiaoling: data curation and data collection. QU Hong: literature search and organization. ZHENG Xianlan: conceptualization and design, study preparation, model construction, manuscript writing, revision, and final approval. All authors read and approved the final manuscript.

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Clinical trial number

Not applicable.

Ethics approval and consent to participate

This retrospective study was approved by the Institutional Review Board of Children's Hospital of Chongqing Medical University (approval number: (2022) Ethical Review (Research) No. 586). All procedures were performed in accordance with the Declaration of Helsinki and relevant guidelines and regulations. Because the study used anonymously collected retrospective data, the requirement for informed consent was waived by the Ethics Committee.

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