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Machine Learning Model for Predicting Operative Duration in Transsphenoidal Neuroendoscopic Pituitary Adenomectomy

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Research Article

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Posted Date: September 28th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10371340/v1

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Additional Declarations: No competing interests reported.

Machine Learning Model for Predicting Operative Duration in Transsphenoidal Neuroendoscopic Pituitary Adenomectomy

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Abstract

Aim: To develop and validate a machine learning model predicting surgical duration for transsphenoidal endoscopic pituitary tumor resection, and assess its utility for nursing management.

Background: Accurate surgical duration prediction is vital for nursing resource allocation and OR scheduling, yet traditional methods often lack precision, leading to workflow inefficiencies and increased nursing burden.

Methods: Retrospective data from 100 patients (2016–2025) yielded 22 preoperative variables. Artificial neural network (ANN) and random forest models were developed and evaluated using R^2, MAE, RMSE, and clinical accuracy (±30/±45 min).

Results: The ANN model outperformed random forest, achieving a test set MAE of 0.636 hours (~38 min). Clinically, 63.3% of predictions were within ±30 min, and 76.7% within ±45 min. Key predictors included tumor recurrence, distance from the third ventricle floor, and the cinch sign.

Conclusion: ANN enables accurate surgical duration prediction, providing objective evidence to optimize nursing schedules, reduce uncertainty, and alleviate perioperative nursing burden.

Implications for Nursing Management: Implementing this model supports precise nursing workload estimation and efficient OR coordination, fostering a more streamlined and lower-burden clinical environment.

Keywords: Transsphenoidal endoscopic surgery; Pituitary adenoma resection; Surgical duration prediction; Nursing management; Operating room scheduling; Machine learning; Artificial neural network

1.Introduction

Pituitary tumors are common benign tumors of the central nervous system, accounting for approximately 10%–15% of intracranial tumors [1]. Transsphenoidal endoscopic surgery has become the preferred treatment modality due to its minimally invasive nature and high safety profile [2]. However, surgical duration may vary by several hours due to factors such as tumor histology, extent of invasion, and surgeon experience [3].

Accurate prediction of surgical duration is crucial for optimizing operating room scheduling, developing individualized anesthesia plans, and enhancing the efficiency of medical resource utilization [4]. Its core value is further reflected in nursing management within the operating room and post-anesthesia care unit [5]. Inefficient surgical scheduling often leads to imbalances in nursing staffing, extended shifts for healthcare personnel, delays in consecutive procedures, and disruptions in postoperative care handover [6]. For head nurses, precise prediction serves as the foundation for creating equitable schedules, ensuring adequate coverage of nursing skill sets, and maintaining patient safety standards. Therefore, developing data-driven, objective prediction tools is not only essential for surgical planning but also critical for enhancing nursing management quality and system efficiency. Traditional surgical duration prediction relies on surgeon experience or single imaging metrics, exhibiting limitations such as high subjectivity and inadequate integration of multidimensional factors, with prediction errors reaching 20%–30% [7]. Machine learning algorithms can automatically uncover latent correlations within data and construct nonlinear predictive models, demonstrating significant advantages in medical prognosis assessment [8]. Artificial neural networks, through their multilayer structure, learn deep feature associations and are particularly suited for analyzing small-sample,

multivariate medical data [9]. Random forests, meanwhile, offer robustness and quantifiable feature importance [10].

Currently, quantitative prediction studies for pituitary tumor surgery duration remain scarce. Existing research primarily focuses on complication prediction or employs linear models with limited accuracy [11-12]. This study aims to construct and compare the predictive performance of artificial neural networks and random forest models, identify key influencing factors, and evaluate the clinical utility of these models from a nursing management perspective. It seeks to provide an evidence-based tool for optimizing perioperative nursing resource allocation.

2.Subjects and Methods

2.1Study Population

This single-center retrospective cohort study included patients who underwent transsphenoidal endoscopic pituitary tumor resection at the Department of Neurosurgery, Second Affiliated Hospital of South China University of Technology between January 2016 and December 2025. Inclusion criteria were: [13] meeting diagnostic and surgical indications per the Chinese Expert Consensus on Surgical Treatment of Pituitary Adenomas (2015 Edition), with postoperative pathological confirmation; first-time recipients of this procedure; complete clinical records; and accurate surgical duration documentation. Exclusion criteria included: concomitant skull base lesions or infections; preoperative nasal abnormalities such as cerebrospinal fluid rhinorrhea; conversion to open craniotomy during surgery; Missing key data.

A total of 100 patients were ultimately included, divided into a training set (70 cases) and a test set (30 cases) at a 7:3 ratio, with an additional 23 cases forming an independent validation set. Baseline characteristics between the training and test sets showed no statistically significant differences ($P > 0.05$), ensuring comparability. This study was approved by the hospital's Medical Ethics Committee (Approval No. 2026040).

2.2 Data Collection and Variable Definition

A standardized data collection form was developed through literature review [14-16] and consultation with three neurosurgery chief physicians, covering 22 variables across four categories:

(1) Patient demographics: age, gender, tumor recurrence status; (2) Tumor characteristics: imaging metrics (tumor size, suprasellar diameter ratio) and morphological features (e.g., smoothness of adenoma margin); (3) Tumor pathology and grading: Knosp grade, histological subtype; (4) Surgical parameters: extended approach, constriction sign, sella turcica base breach. Specific variable definitions and scoring methods are detailed in Table 1.

Table 1: Feature Variable Assignment Table

Category	Variable Name	Variable Type
Patient Basic Information	Age	Continuous variable
	Recurrence	Binary variable
Tumor Characteristics	Size	Continuous variable
	Suprasellar Vertical Ratio	Continuous variable
	Distance to Third Ventricle Floor	Continuous variable
	Distance to Commissure	Continuous variable
	Distance to Foramen of Monro	Continuous variable
	Smooth Upper Margin of Adenoma	Binary variable
	Lobulation (Daughter Tumor)	Binary variable
	Tumor Texture	Binary variable
Tumor Pathology and Grading	Knosp Grade	Binary variable
	Pathological Type	Binary variable
	Clinical Type	Binary variable
Surgical-related parameters	Extended Approach	Binary variable
	Waist Sign	Binary variable
	Sellar Floor Penetration	Binary variable
	Clivus Invasion	Binary variable
	Intact Diaphragma Sellae	Binary variable
	Hemorrhage	Binary variable
	Intraoperative CSF Leak	Binary variable
	Skull Base Reconstruction Method	Binary variable
	Sphenoid Sinus Type	Binary variable
	Tumor Resection Rate	Binary variable

Category	Variable Name	Variable Type
	Suprasellar Resection Rate	Binary variable

2.3Definition of Target Variables

Surgical duration is defined as the total time from the initiation of the surgical incision to the completion of suturing and dressing (＜4 hours). Data were sourced from the surgical anesthesia management system and independently verified by two researchers. Disputes were resolved by consulting original records [17].

2.4Data Preprocessing and Feature Selection

Data preprocessing adhered to principles of completeness, consistency, and standardization: continuous variables with missing rates ≤20% were imputed using multiple imputation methods, while categorical variables were imputed with the mode. Outliers were identified via box plots and corrected or removed after verification. Categorical variables underwent one-hot encoding, and continuous variables were normalized to 0–1 [18–19]. Feature selection employed a “filtering + embedding” strategy: first, correlations between each feature and the target variable were calculated, and features with absolute correlation coefficients <0.1 were discarded; subsequently, Lasso regression was used to further screen core features, eliminating redundant variables [20-21].

2.5Model Construction and Evaluation

2.5.1Dataset Partitioning and Validation Strategy

The training set is used for model training and hyperparameter tuning, the test set for preliminary performance evaluation, and an independent validation set for verifying model generalization. Five-fold cross-validation is employed to optimize hyperparameters and prevent overfitting.

2.5.2Model Construction

Artificial Neural Network Model: The input layer has the same number of nodes as the core features, with two hidden layers (64 and 32 neurons respectively). The activation function uses ReLU, and the output layer consists of a single neuron (linear activation function). The loss function is mean squared error, with Adam as the

optimizer (learning rate 0.001). Training runs for 100 epochs with a batch size of 16, incorporating early stopping and Dropout (dropout rate 0.2).

Random Forest Model: Serving as a control model, it employs 100 decision trees with a maximum depth of 8, constructed using bootstrap sampling. Hyperparameters such as maximum number of features, minimum number of splits, and minimum leaf node size were optimized via grid search combined with 5-fold cross-validation. No feature scaling is required; both continuous and categorical features can be processed simultaneously. Feature importance is evaluated using Gini impurity or average precision decay.

2.6Statistical Analysis and Computing Environment

Statistical analysis was performed using SPSS 26.0 and Python 3.7. Quantitative data are expressed as mean ± standard deviation, with intergroup comparisons conducted using t-tests. Qualitative data are presented as case numbers (percentages), with intergroup comparisons performed using χ^2 tests. $P < 0.05$ was considered statistically significant.

Computing Environment: PyCharm 2024.1.7 integrated development environment; Hardware configuration: Intel Core i5-13490F CPU, 16GB RAM, Windows 11 operating system; Artificial neural network models were constructed using TensorFlow 2.8.0. The Scikit-learn 1.0.2 library was employed for building random forest models and performing data preprocessing. Matplotlib 3.5.2 and Seaborn 0.11.2 were utilized for visualization.

2.7Experimental Design and Visualization

The artificial neural network architecture was optimized using an enumeration approach. Different combinations of hidden layer counts (3–6 layers) and neuron numbers were tested, with each combination trained five times. The architecture yielding the lowest validation set loss was selected (6 hidden layers with neuron counts of 512, 384, 256, 128, 64, and 32). .

Visual analysis included plotting training loss curves, scatter plots of predicted vs. actual values, residual distribution plots, feature importance ranking charts, and ROC curves. All charts adhered to academic publication standards.

3. Results

3.1 Artificial Neural Network Model Results

The artificial neural network model trained stably, with a training loss of 0.6576 and a validation loss of 0.9260, demonstrating good convergence without significant overfitting (Figure 1). The test set achieved a mean absolute error of 0.636 hours, a root mean square error of 1.255 hours, and an R^2 value of 0.321. Predicted values and actual values clustered closely around the ideal prediction line (Figure 2).



Figure 1: In-Depth Analysis of the Model Training Process (Training History Chart)

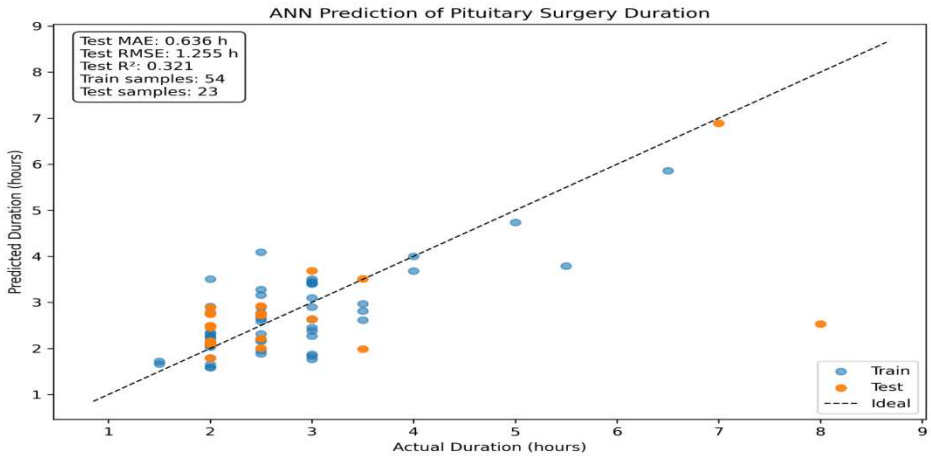


Figure 2: Consistency Analysis of Predicted vs. Actual Values

Residual analysis indicates a mean residual of 0.2721 hours with a standard deviation of 1.0965 hours, randomly distributed near zero with no discernible trend (Figure 3). Prediction errors exhibit near-normal distribution, with over 90% of absolute errors falling below 3 hours (Figure 4).

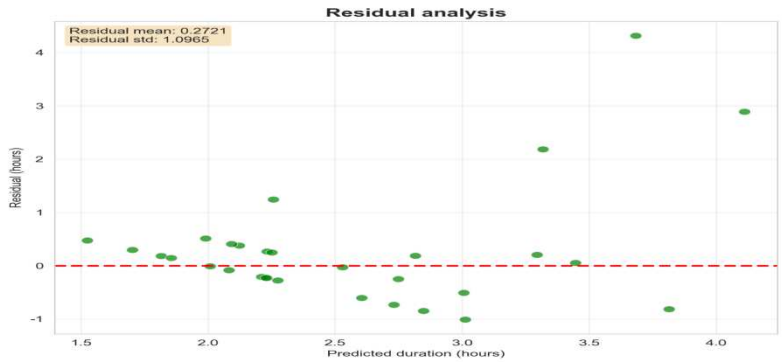


Figure 3: Verification of Residual Randomness (Residual Analysis Plot)

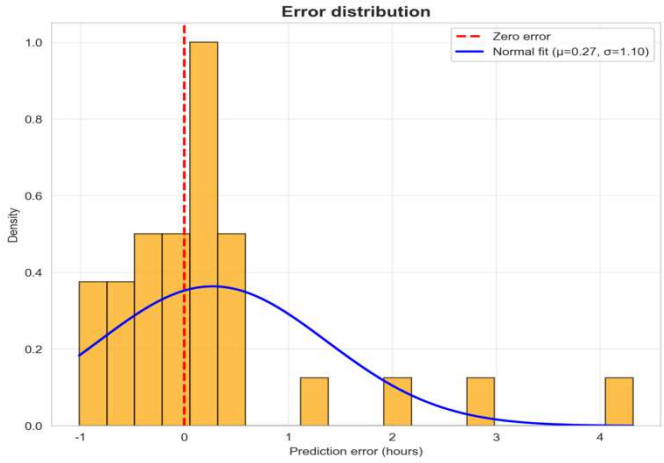


Figure 4: Error Distribution Characteristics (Error Distribution Diagram)

Feature importance ranking revealed tumor recurrence status, distance to the third ventricle floor, waist sign, distance to the interventricular foramen, and suprasellar pituitary diameter ratio as core predictive factors (Figure 5). In clinical error threshold analysis, prediction accuracy within ±30 minutes and ±45 minutes reached 63.3% and 76.7%, respectively (Figure 6). Most cases exhibited errors ≤30 minutes, with only a minority exceeding 60 minutes, indicating controllable error margins (Figure 7).

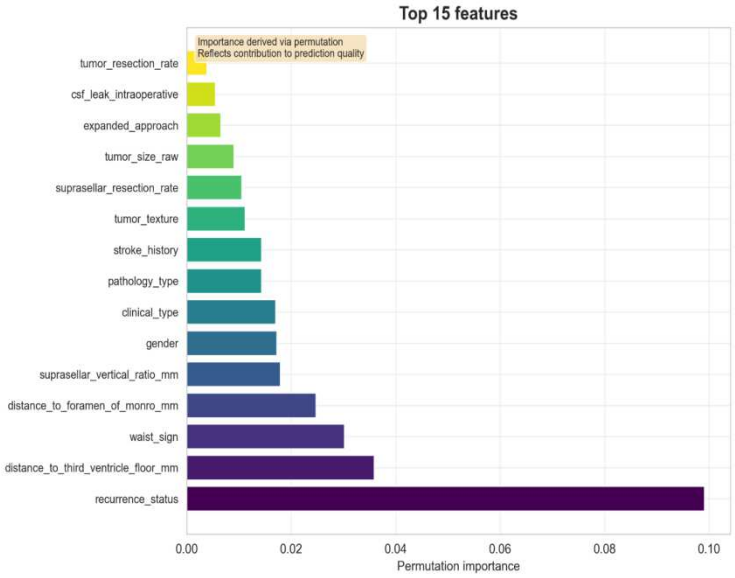


Figure 5: Contribution Ranking of Key Features (Top 15 Features Chart)

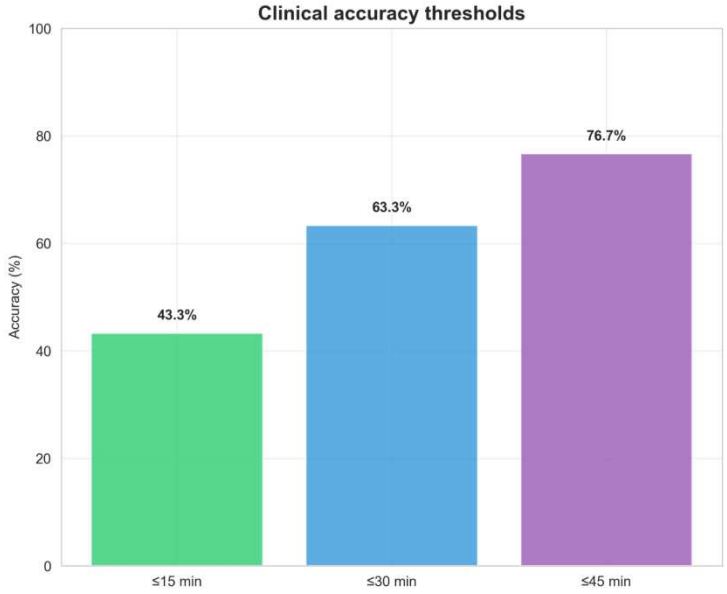


Figure 6: Actual Values of Clinical Accuracy Thresholds (Clinical Accuracy Thresholds Figure)

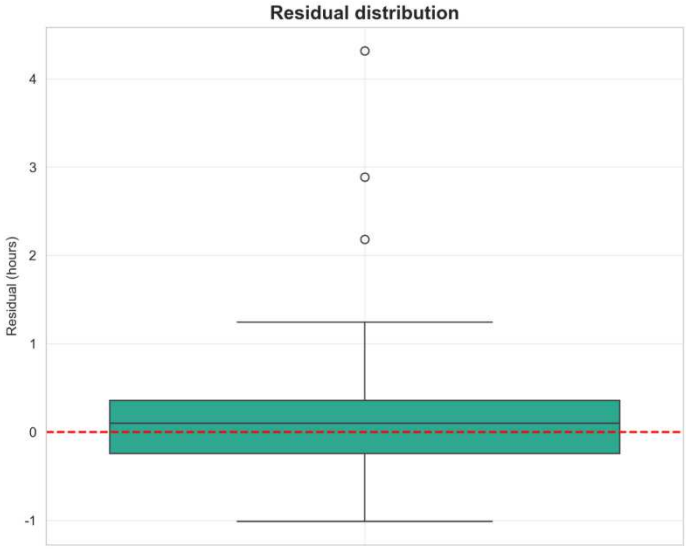


Figure 7: Distribution Characteristics of Residuals (Residual Distribution Plot)

3.2 Random Forest Model Results

The Random Forest model achieved an R^2 of 0.326 on the test set with a mean absolute error of 0.806 hours, exhibiting significant prediction bias for prolonged surgeries (Figure 8). The residual distribution exhibited left skewness (Figures 9 and 10). Accuracy rates at ±15-minute, ±30-minute, and ±45-minute error thresholds were 27.8%, 55.6%, and 72.2%, respectively (Figure 11). Feature importance rankings were largely consistent with those from the artificial neural network model (Figure 12).

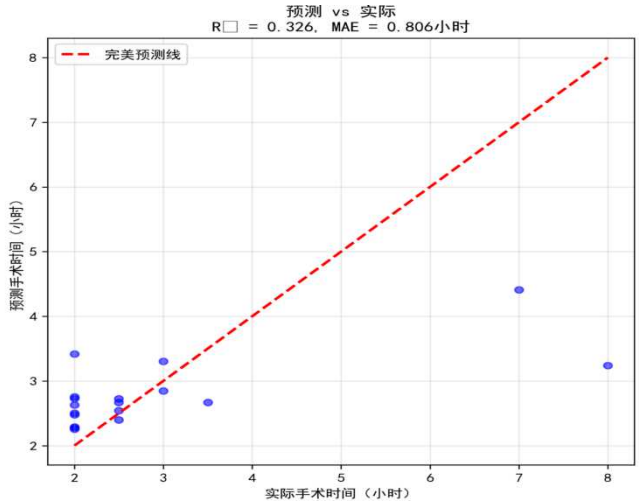


Figure 8: Scatter Plot of Predicted Surgery Duration vs. Actual Surgery Duration

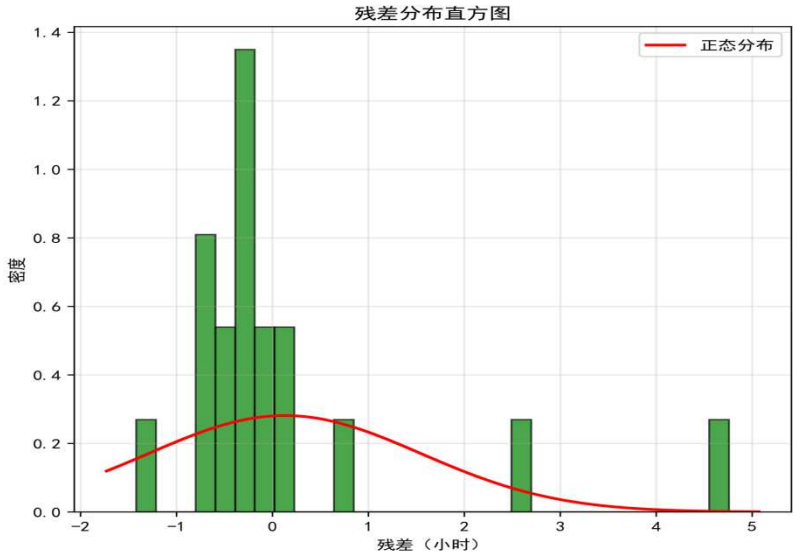


Figure 9: Residual Distribution Histogram

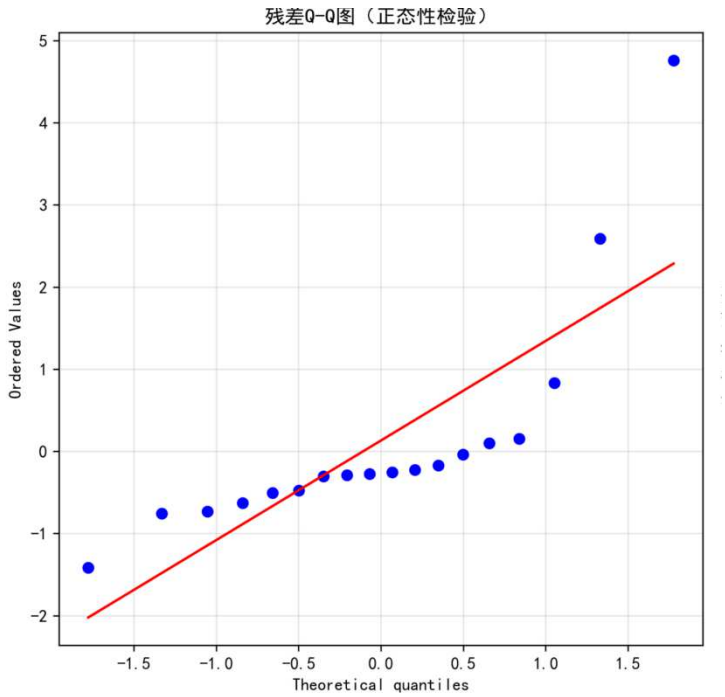


Figure 10: Residual Q-Q Plot (Normality Test Plot)

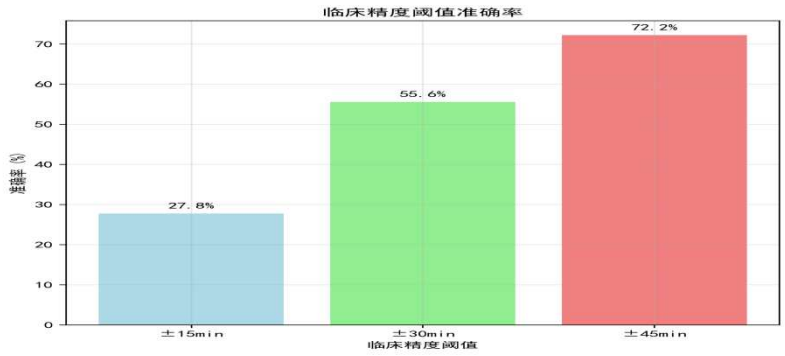


Figure 11: Accuracy of Random Forest Model at Clinical Thresholds

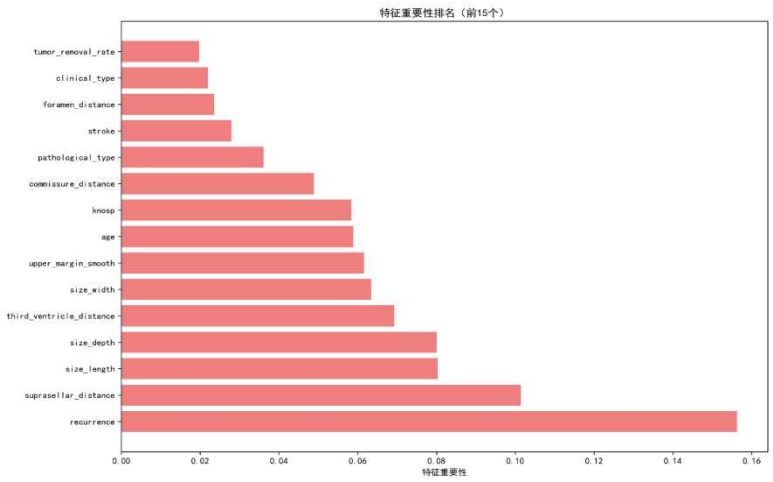


Figure 12 Feature Importance Metrics for the Random Forest Model

3.3 Model Performance Comparison

As shown in Table 2, the artificial neural network model outperformed the random forest model in terms of mean absolute error, root mean square error, and pseudo-AUC, demonstrating superior overall predictive performance.

Table 2 Comparison of Model Performance Metrics (Mean ± Standard Deviation)

Model	Dataset	R^2	MAE	RMSE	伪 AUC
ANN	Test set	0.321±0.041	0.636±0.048	1.255±0.062	0.812±0.025
	Validation set	0.305±0.045	0.682±0.053	1.312±0.068	0.798±0.028
RF	Test set	0.326±0.038	0.806±0.051	1.374±0.065	0.780±0.027
	Validation set	0.283±0.043	0.854±0.056	1.426±0.071	0.765±0.030

4. Discussion

The artificial neural network model developed in this study demonstrated excellent performance in predicting the duration of transsphenoidal endoscopic pituitary tumor resection. The average absolute error on the test set was only 38 minutes, with a clinical accuracy rate of 76.7% within ±45 minutes, significantly outperforming both the random forest model and traditional empirical estimation methods. The model successfully captured the complex nonlinear relationship between clinical features and surgical duration. Its core predictors align closely with clinical practice: recurrent tumors increase surgical dissection difficulty due to tissue

adhesions; tumor proximity to critical structures like the third ventricle floor and interventricular foramen affects surgical precision and risk; morphological features such as the constriction sign reflect tumor growth patterns and texture—all directly correlate with operative time.

From a nursing management perspective, the machine learning prediction tool developed in this study offers significant practical advantages and diverse application value. First, by utilizing objective preoperative clinical characteristics as input, the model's output of surgical duration predictions overcomes the limitations of traditional approaches reliant on surgeons' subjective experience and rough statistical analysis of historical data. It provides standardized, repeatable, and objective evidence for nursing management decisions, effectively reducing subjectivity and randomness in scheduling decisions. Second, the model accurately identifies high-risk cases for prolonged surgeries (e.g., recurrent tumors, tumors in close proximity to the floor of the third ventricle). Nursing administrators can use this information to preemptively schedule surgical windows, allocate experienced scrub and circulating nurse teams, and optimize instrument preparation and intraoperative coordination workflows to ensure safe and efficient surgical procedures. Additionally, the model's predicted time windows provide clear scheduling references for head nurses to: - Create precise nursing staffing schedules - Coordinate post-anesthesia care unit (PACU) bed resources - Plan instrument preprocessing and sterilization workflows This reduces last-minute scheduling changes, alleviates nursing staff workload, enhances overall OR operational efficiency, and improves continuity of perioperative patient care. Third, the model's conceptual framework and methodology demonstrate strong scalability and adaptability across surgical scenarios, positioning it as a universal tool for optimizing perioperative nursing resource allocation that can be extended to other surgical specialties. Transnasal transsphenoidal endoscopic surgery is a minimally invasive cranial base procedure. Its duration is influenced by multidimensional factors including tumor characteristics, anatomical structures, and surgical complexity. These factors exhibit similar patterns to those affecting minimally invasive elective surgeries in gastrointestinal, urological, and orthopedic fields (e.g., laparoscopic gastrointestinal

tumor resection, percutaneous nephrolithotomy, arthroscopic ligament reconstruction). — These procedures share distinct preoperative quantifiable characteristics (e.g., lesion size, location, histological type, anatomical variations) and exhibit nonlinear, multifactorial interactions influencing operative duration. The established technical pathway—"preoperative feature selection → machine learning model construction → clinical accuracy validation"—can be directly applied to these surgical scenarios. By adjusting the feature variable system (e.g., replacing with lesion characteristics and procedure-specific parameters relevant to each surgery) and retraining/validating the model according to each procedure's clinical characteristics, precise prediction of diverse surgical durations becomes achievable. Furthermore, the model can be integrated into hospital operating room management information systems to enable automated, intelligent prediction of surgical duration. By linking with nursing scheduling systems and OR dispatch systems, it drives the digital and refined upgrading of overall perioperative management within hospitals. This provides technical support for the coordinated allocation of nursing resources across multiple departments and the efficient operation of operating rooms. Its application value extends beyond a single type of surgery, offering a feasible solution for enhancing the overall quality of nursing management within hospitals.

This study has certain limitations: First, it is a single-center retrospective study involving only 100 patients from the Department of Neurosurgery at the Second Affiliated Hospital of South China University. The sample size is limited, and the results may be subject to selection bias due to the influence of single-center patient characteristics, standardized medical protocols, and homogeneous nursing workflows. The model's generalizability requires further validation. Additionally, all surgical procedures were performed by the same neurosurgery team, ensuring high consistency in the surgeon's operational habits, surgical proficiency, and team coordination efficiency. Key variables affecting surgical duration, such as differences in surgeon operating styles, experience levels, and collaboration efficiency among different surgical teams, were not included. Consequently, the predictive accuracy of the model may be compromised when applied to other surgical teams or healthcare

institutions. Second, nursing-sensitive human factors—such as nursing team composition, nursing staff proficiency, interdisciplinary collaboration efficiency, and learning curves—were excluded. These factors are closely linked to surgical duration and constitute core nursing management concerns. Future models should integrate such variables to enhance alignment with clinical nursing practices. Finally, artificial neural network models inherently suffer from weak interpretability, potentially hindering clinical nurses and surgeons' understanding and acceptance of predictive outcomes. Future approaches should incorporate explainable AI techniques like SHAP or LIME to visualize predictive logic and feature contributions, thereby boosting clinical teams' trust in and willingness to adopt the model's predictions.

In summary, machine learning models, particularly artificial neural networks, can accurately predict the duration of transsphenoidal endoscopic pituitary tumor resection surgery. This provides a quantitative tool for nursing management, driving the transformation of nursing scheduling from reactive response to predictive resource management. The model's construction methodology and application approach can be extended to various types of minimally invasive elective surgeries, offering a new pathway for the refinement and digitalization of overall operating room nursing management in hospitals. Future research should involve multicenter, large-sample collaborations incorporating clinical data from diverse hospitals and surgical teams. By integrating variables such as surgeon characteristics and nursing team factors, the model structure can be optimized and its interpretability enhanced. This will further improve clinical applicability and generalization capabilities, enabling better support for perioperative nursing resource allocation and efficient OR management. Ultimately, this approach aims to achieve dual objectives: reducing healthcare professional burnout and elevating patient care quality.

5. Conclusion

This study successfully constructed and validated two machine learning models—artificial neural networks and random forests—for predicting the duration of transsphenoidal endoscopic pituitary tumor resection. The artificial neural network model demonstrated superior performance, achieving an average absolute error of

0.636 hours (approximately 38 minutes) on the test set, achieving 76.7% clinical accuracy within ±45 minutes. It identified tumor recurrence status, anatomical distance from the third ventricle floor, and the constriction sign as core predictors of surgical duration. This model provides objective quantitative evidence for perioperative nursing management, enabling nursing administrators to precisely schedule surgeries, optimize human and equipment resource allocation, and reduce scheduling uncertainty. It facilitates the transition from experience-driven to data-driven nursing scheduling, enhancing operating room efficiency and perioperative care quality. Additionally, the technical pathway established in this study—involving preoperative feature screening and machine learning model construction—can be extended to minimally invasive elective surgeries in gastrointestinal, urological, and orthopedic fields, demonstrating strong potential for clinical application.

Limitations such as single-center recruitment, small sample size, and homogeneity of surgical teams restrict the model's generalization capability, which requires further improvement. Future efforts should focus on expanding sample size through multicenter collaboration, incorporating key variables such as surgeon operational characteristics and nursing team composition to optimize the model. Integrating techniques like SHAP and LIME to enhance model interpretability, alongside integrating the model with operating room management systems, will further leverage its role in refined nursing resource management. This approach provides robust technical support for building an efficient, low-burden clinical care environment.

Declarations

Abbreviations

ANN, Artificial Neural Network; RF, Random Forest; ReLU, Rectified Linear Unit; SHAP, SHapley Additive exPlanations; LIME, Local Interpretable Model-agnostic Explanations; R^2, Coefficient of Determination; MAE, Mean Absolute Error; RMSE, Root Mean Square Error; AUC, Area Under the Curve; ROC,

Receiver Operating Characteristic; OR, Operating Room; CSF, Cerebrospinal Fluid; PACU, Post-Anesthesia Care Unit; CPU, Central Processing Unit; RAM, Random Access Memory

Ethics approval and consent to participate

This study was approved by the Medical Ethics Committee of The Second Affiliated Hospital, University of South China (Approval No. 2026040). All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and/or analysed during the current study are not publicly available due to the privacy protections of human participants, but are available from the corresponding author on reasonable request.

Competing Interests

The authors declare that they have no competing interests.

Funding

No funding was obtained to support this study.

Authors' contributions

Yunbo Deng contributed to the study conception and design, data collection, and manuscript drafting. Xinyue Liu contributed to data analysis and interpretation. Min Zhou contributed to data collection and critical revision of the manuscript. Yan Wang contributed to the study conception, design, and supervision, and provided critical feedback on the manuscript. All authors read and approved the final manuscript.

Acknowledgements

Not applicable.

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