

Deep learning-based automatic segmentation of bronchial arteries and identification of culprit bleeding vessels in hemoptysis: a clinical feasibility study

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Abstract

Background

Bronchial artery (BA) abnormalities are the main cause of massive hemoptysis. Accurate preoperative segmentation and culprit vessel identification are critical for bronchial artery embolization (BAE). Conventional manual segmentation is time-consuming and subjective, lacking standardized automated workflows for emergency settings. This study aimed to develop an end-to-end deep learning pipeline for automatic BA segmentation and culprit hemoptysis vessel identification.

Methods

A retrospective single-center study enrolled 140 hemoptysis patients who underwent BA-CTA and BAE. A 3D V-Net with attention and cascade learning was built for automated BA segmentation. After vessel splitting, radiomic features were extracted and selected via mRMR-LASSO to train machine learning classifiers for culprit vessel diagnosis. Segmentation accuracy, diagnostic performance, and time efficiency were validated against manual segmentation and DSA gold standard.

Results

The segmentation model yielded a Dice similarity coefficient (DSC) of 0.83 ± 0.21 and a 95% Hausdorff distance (95% HD) of 14.48 mm. The logistic regression classifier achieved optimal diagnostic performance, with an area under the curve (AUC) of 0.82, a sensitivity of 0.87, a specificity of 0.69, and an accuracy of 0.78 in the test set, showing non-inferior performance compared with senior radiologists (all $P > 0.05$). The mean processing time per case was 2.58 minutes for the AI pipeline, 6.27 minutes for senior radiologists, and 16.30 minutes for radiologic technologists.

Conclusion

This fully automated pipeline enables rapid, accurate BA segmentation and culprit vessel identification with performance equivalent to senior radiologists and drastically improved efficiency. It provides a reliable tool for emergency hemoptysis management and precise preoperative planning for BAE.

Introduction

Pathological dilatation, tortuosity, and neovascularization of the bronchial artery (BA) are closely associated with multiple pulmonary disorders, including bronchiectasis, pulmonary tuberculosis, and lung neoplasms, and constitute the leading etiology of hemoptysis [1]. According to epidemiological data, 5%–14% of patients with hemoptysis develop life-threatening massive hemoptysis, with an in-hospital mortality rate of 9%–38% [2]. Notably, more than 90% of bleeding sources in massive hemoptysis are derived from abnormal BA lesions. Owing to the high prevalence of anatomical variations and small caliber of the BA, rapid identification of the culprit bleeding vessels and underlying etiologies remains difficult, presenting substantial challenges to the emergency diagnosis and targeted treatment of hemoptysis [3]. Bronchial artery embolization (BAE) is currently the first-line minimally invasive strategy for hemoptysis refractory to medical therapy, characterized by minimal invasiveness, high hemostatic success rate, and low complication risk [4, 5]. Accordingly, accurate preoperative segmentation of the BA, clear delineation of its anatomical architecture, and rapid identification of the culprit bleeding vessels represent the essential prerequisites for precise BAE execution, reducing postoperative recurrence, and improving clinical outcomes.

Computed tomography angiography (CTA) is a rapid, non-invasive imaging modality that offers distinct advantages in detecting ectopic-origin BAs, non-bronchial systemic collateral arteries, and pulmonary pseudoaneurysms [6, 7]. It has become the preferred imaging technique for clinical evaluation of BA anatomy and localization of bleeding sources in hemoptysis. However, in current clinical practice, segmentation and three-dimensional (3D) reconstruction of the BA still rely entirely on manual delineation by experienced radiologists. This approach is not only cumbersome and time-consuming, failing to meet the demand for rapid interventional planning in emergency hemoptysis, but also yields results highly dependent on operator experience and proficiency. Subjective variability is considerable, and inter-observer agreement is difficult to maintain. Furthermore, no standardized quantitative criteria exist for identifying culprit hemoptysis vessels, which are currently determined mainly by radiologists' empirical judgment. In cases with complex anatomical variations or multi-vessel supply, missed or misdiagnosed culprit vessels are common, which further compromises the hemostatic efficacy of BAE and patient prognosis [8].

In recent years, artificial intelligence (AI) technologies based on deep learning have advanced rapidly in medical imaging and demonstrated reliable, high-efficiency performance in vascular segmentation, lesion detection, and computer-aided diagnosis [9–11]. In cardiovascular and thoracic vascular imaging, AI has enabled automated segmentation and pathological assessment of coronary arteries, cervicocerebral vessels, and pulmonary arteries, achieving diagnostic performance comparable to senior radiologists while markedly reducing post-processing time [12–14]. Deep learning has also achieved favorable results in automatic segmentation of pulmonary vessels and small-volume structures, providing a feasible technical framework for segmenting small-caliber, tortuous, and complex BAs [15–18]. Nevertheless, research on automated BA segmentation and intelligent identification of culprit hemoptysis vessels remains limited. No end-to-end AI workflow directly applicable to emergency clinical settings has been established, which restricts the rapid diagnosis and treatment of hemoptysis.

To address these unmet clinical needs and technical limitations, this study aims to develop a fully automated, standardized end-to-end deep learning pipeline based on deep learning for intelligent BA segmentation and automatic identification of culprit hemoptysis vessels. The pipeline employs a 3D V-Net

architecture integrated with attention mechanisms and cascade learning to achieve accurate automated segmentation of the BA, combined with morphological algorithms for individual vessel branch separation. Finally, a machine learning classifier is constructed using radiomic features to enable rapid and intelligent identification of culprit vessels. This study will systematically evaluate the segmentation accuracy, diagnostic performance, and clinical time-efficiency of the proposed pipeline and validate its clinical feasibility. We aim to provide a robust technical tool for rapid diagnosis and treatment of emergency hemoptysis and precise preoperative planning for BAE, thereby overcoming the limitations of conventional manual procedures, including excessive time consumption, high subjectivity, and low reliability in culprit vessel identification.

Materials and Methods

Ethics Statement

This retrospective single-center observational study was conducted in strict compliance with the ethical principles of the Declaration of Helsinki and its subsequent amendments. The study protocol was approved by the Ethics Committee of the People's Hospital of Xiangxi Tujia and Miao Autonomous Prefecture (Ethics Approval No. XXZRY-LCKY-2025-71). Given the retrospective design of the study, all clinical and imaging data of enrolled patients were fully anonymized, and the Ethics Committee granted a waiver of written informed consent from participants. No study-driven interventional examinations or treatments were performed on the subjects throughout the study period, and all imaging examinations and treatment regimens were part of routine clinical practice.

Patient data

Patients admitted to our hospital for hemoptysis between January 2022 and December 2024 were consecutively and retrospectively enrolled in this study.

Inclusion criteria: (1) Patients admitted for hemoptysis who met the diagnostic criteria for hemoptysis specified in the *9th edition of Internal Medicine*; (2) Patients scheduled to undergo BAE, who completed bronchial artery computed tomography angiography (BA-CTA) within 1 week before the procedure, with image quality sufficient for quantitative analysis; (3) Patients with complete clinical data, imaging data, and intraoperative digital subtraction angiography (DSA) data, where the interval between CTA and DSA acquisition was no more than 72 hours, with no missing key clinical or imaging information.

Exclusion criteria: (1) Renal insufficiency (serum creatinine > 152 $\mu\text{mol/L}$) or intolerance to iodinated contrast media; (2) Concomitant uncontrolled severe arrhythmia or organic heart disease that impairs CTA image quality and vascular assessment; (3) A history of allergy to iodinated contrast media or previous severe adverse reactions to contrast media; (4) Uncontrolled hyperthyroidism; (5) Pregnant or lactating women; (6) CTA images with severe motion artifacts or excessive noise that preclude BA segmentation and subsequent analysis.

Image acquisition

All patients underwent BA-CTA examination using a dual-source CT scanner SOMATOM Force (Siemens Healthineers, Forchheim, Germany). Prior to scanning, all metallic foreign bodies in the thoracic region were removed, and standardized breathing training was performed to ensure patients could maintain adequate breath-holding during image acquisition. The scan range for both non-contrast and contrast-enhanced acquisitions extended from the middle cervical segment to the lung base. Image acquisition was automatically triggered using a bolus tracking technique, with a region of interest (ROI) positioned in the descending aorta; scanning was initiated automatically when the CT attenuation within the ROI reached 120 HU, with an additional delay of 5 to 7 seconds. Non-ionic iodinated contrast medium iohexol (350 mgI/ml) was administered with a total volume of 60 ml delivered at a flow rate of 5.0 ml/s, followed by a 30 ml saline flush at the same flow rate. The data were reconstructed with a slice thickness of 1 mm and a slice interval of 0.7 mm, and all reconstructed images were transferred to the 3D Slicer (version 5.4.0) post-processing workstation for subsequent analysis.

Image Analysis

Manual segmentation of the BA was independently performed by two radiologists with over 5 years of experience in thoracic vascular imaging diagnosis using 3D Slicer software, with both radiologists blinded to the patients' clinical data, DSA findings, and treatment outcomes. The annotation scope covered all BA trunks and ectopic-origin feeding arteries with a diameter ≥ 1.5 mm, and the contour delineation was performed on the extrapulmonary lumen from the aortic origin of the vessel to the hilar level. For cases with discrepancies in the annotation results between the two radiologists, a senior radiologist with more than 20 years of experience in thoracic imaging diagnosis conducted the final review and adjudication. The consensus annotation results were established as the reference standard (ground truth for spatial localization in the vessel segmentation task) for the training and testing of the deep learning model. The inter-observer agreement of the manual segmentation results between the two radiologists was evaluated using the intraclass correlation coefficient (ICC), and an ICC value > 0.75 was defined as indicating good agreement. In this study, intraoperative DSA findings served as the gold standard for the diagnosis of culprit bleeding vessels in hemoptysis. A feeding artery was determined as a culprit vessel if it met the following criteria: intraoperative angiography showed contrast extravasation, abnormal dilatation and tortuosity, tumor staining, or aneurysm formation in the vessel, with the blood supply range matching the bleeding site of the patient.

Intelligent Segmentation Model for Bronchial Arteries

we adopted a 3D V-Net architecture, incorporating an attention mechanism within the skip connections and employing a cascade learning strategy to achieve accurate segmentation of bronchial arteries in CTA images (Fig. 1).

Data Preprocessing

Data Standardization: First, the voxel resolution of all CTA images was uniformly resampled to $1.0 \times 1.0 \times 1.0 \text{ mm}^3$ to mitigate variability arising from differences in imaging equipment and scanning protocols. Subsequently, each CT image was resized to a consistent dimension of 512×512 pixels to facilitate processing by the network. Additionally, to enhance the model's learning performance and generalization capability, pixel intensities were normalized using standardized window width and window level settings (window width: 400 Hounsfield Units [HU]; window level: 40 HU).

Data Augmentation: To expand the training dataset and improve model generalization, one or more of the following image transformations were randomly applied during training for data augmentation: $\boxtimes$ horizontal flipping; $\boxtimes$ vertical flipping; $\boxtimes$ image scaling (scaling factor range: 0.8–1.2); and $\boxtimes$ image cropping.

Model Construction and Training

In this study, a 3D V-Net served as the backbone architecture for bronchial artery segmentation. Based on a fully convolutional framework, this network performs end-to-end dense prediction of 3D images through an encoder–decoder structure. Skip connections are employed to integrate shallow detail features from the encoder with deep semantic features from the decoder, thereby mitigating the loss of fine structural detail commonly encountered in vessel segmentation tasks.

To further enhance performance, an attention mechanism was integrated into the skip connection pathways. This mechanism adaptively amplifies the feature weights corresponding to vascular regions while suppressing background tissue signals, thereby improving the network's sensitivity to slender bronchial arteries. A cascade learning strategy was implemented: a coarse segmentation network first localized the bronchial artery ROI, followed by a fine segmentation network that refined vessel boundary delineation, thereby improving overall segmentation accuracy.

Model training was conducted using a 5-fold cross-validation strategy. The training dataset was randomly partitioned into five equally sized subsets. In each iteration, four subsets were used for training and the remaining subset for validation, with this process repeated across all five folds. Hyperparameter optimization was guided by the average performance across the five validation folds to ensure model stability and generalizability.

A hybrid hyperparameter tuning approach combining grid search and Bayesian optimization was employed. Initially, a grid search was performed to coarsely identify optimal ranges for core hyperparameters, including learning rate, batch size, and regularization coefficient. Subsequently, Bayesian optimization was applied within these ranges to fine-tune the hyperparameters, using the validation set's Dice similarity coefficient (DSC) as the objective function. The final training configuration corresponded to the hyperparameter combination that maximized the objective function.

The final training hyperparameters were as follows: the AdamW optimizer was selected, with an initial learning rate of 1×10^{-4} and a cosine annealing schedule for learning rate decay. The batch size was set to 2, and the weight decay coefficient was 1×10^{-5} . Training proceeded for a maximum of 100 epochs, with an early stopping strategy (patience = 15 epochs) applied to terminate training when validation performance ceased to improve, thereby preventing overfitting.

Loss Function

To address challenges such as the low proportion of positive bronchial artery samples, the elevated risk of missed segmentation of slender vessels, and the tendency for topological discontinuities in segmentation outputs, the loss function in this study comprised a weighted combination of Tversky Loss and CIDice Loss. The weighting coefficients were set to 1:1 based on hyperparameter tuning. The total loss function is defined as:

Loss = Tversky Loss + CIDice Loss

where:

$$\text{Tversky Loss} = \frac{TP}{TP + \alpha \times FP + \beta \times FN}$$

In this formulation, TP, FP, and FN denote true positives, false positives, and false negatives, respectively. The coefficients α and β (set to 0.3 and 0.7, respectively) were tuned to prioritize the detection of small vessels by penalizing false negatives more heavily than false positives.

CIDice Loss is designed to enforce topological consistency based on vessel centerline structure and is defined as:

CIDice Loss =

$$\frac{2 \times ||\text{Centerline}(\hat{Y}) \cap \text{Centerline}(Y)||}{||\text{Centerline}(\hat{Y})|| + ||\text{Centerline}(Y)||}$$

Here, Centerline(.) denotes the vessel centerline extracted via skeletonization. This component encourages topological continuity between the predicted segmentation and the ground truth.

In the post-processing stage, only 3D connected components with a volume of at least 10 voxels were retained as segmented vessels. Additionally, a morphological closing operation (using a spherical structuring element with a radius of 1 voxel) was applied to fill small discontinuities in the segmentation output.

Intelligent Identification Model for Hemoptysis Culprit Vessels

Building upon the automated bronchial artery segmentation framework, this study first performed individual vessel branch separation using morphological registration and graph-based algorithms. Subsequently, a machine learning model leveraging radiomics features was developed to achieve binary classification and identification of culprit versus non-culprit vessels.

Bronchial Artery Branch Splitting

Aorta Segmentation: The aorta segmentation model available via the United Imaging Intelligence Research Portal (<https://www.uui-ai.com/research.html>) was utilized to automatically extract the aortic ROI.

Origin Point Localization: The intersection between the binarized bronchial artery segmentation and the aortic segmentation was computed. Voxels within this intersection were subjected to cluster analysis, and the cluster centroid was designated as the aortic origin point of the bronchial artery.

Branch Splitting: A 3D skeletonization algorithm was applied to extract the topological centerline of each vessel. Using a graph-based minimum cut algorithm with the origin point as the root node, automated separation of individual vessel branches was performed according to the criteria of “single origin point, independent vascular course, and independent blood supply territory.” Small-caliber communicating branches and collateral vessels (diameter < 1 mm) were excluded. The resulting branch splitting was reviewed and manually corrected by two radiologists, each with over five years of experience in chest imaging diagnosis, to ensure anatomical accuracy.

Radiomics Feature Extraction

Radiomics features were extracted using the PyRadiomics toolbox in Python 3.7, with many features defined in accordance with the Initiative for Standardization of Biomarkers in Imaging (IBSI). For each image, three categories of radiomics features were extracted: 18 first-order features, 14 shape features, and 72 texture features. The texture features comprised 21 Gray Level Co-occurrence Matrix (GLCM) features, 14 Gray Level Dependence Matrix (GLDM) features, 16 Gray Level Run Length Matrix (GLRLM) features, 16 Gray Level Size Zone Matrix (GLSZM) features, and 5 Neighborhood Gray Tone Difference Matrix (NGTDM) features.

Additionally, 14 image filters were applied, and all features except shape features were extracted from the filtered images. This yielded a total of 2,264 radiomics features per patient. All feature extraction was conducted via the research portal (<https://www.uui-ai.com/research.html>).

Feature Selection and Model Construction

Z-score normalization was applied to reduce dimensional discrepancies among features, and radiomics features were cleaned to minimize the influence of outliers and missing values. A cascaded feature reduction strategy combining minimum Redundancy Maximum Relevance (mRMR) and Least Absolute Shrinkage and Selection Operator (LASSO) was employed to eliminate redundant features and enhance model efficiency:

Step 1: Initial feature screening was performed using the mRMR algorithm, retaining 50 candidate features. Selection criteria included a high correlation with culprit vessel status (Pearson correlation coefficient $|r| > 0.3$) and low inter-feature redundancy (mutual information < 0.5).

Step 2: Fine-grained selection was conducted using LASSO regression. A regularization path was constructed via 10-fold cross-validation, and the optimal regularization parameter λ was determined according to the “minimum mean squared error” criterion. Features with non-zero coefficients in the final model were retained.

Using the selected features, classification models were constructed employing logistic regression, decision tree, random forest, and support vector machine algorithms.

Evaluation Metrics

The performance of the proposed deep learning–based end-to-end system was comprehensively assessed across three dimensions: segmentation accuracy, diagnostic efficacy for culprit vessel classification, and clinical timeliness. All metrics were computed using data from the independent test set.

Segmentation Performance Metrics

Using consensus annotations from multiple radiologists as the gold standard, the Dice similarity coefficient (DSC) was employed to quantify spatial overlap between the segmentation results and the reference standard. The 95% Hausdorff Distance (95% HD) was used to evaluate boundary alignment accuracy. Higher DSC values and lower 95% HD values indicate superior segmentation performance.

Classification and Diagnostic Efficacy Metrics

With intraoperative Digital Subtraction Angiography (DSA) findings serving as the reference standard for culprit vessel identification, the Area Under the Receiver Operating Characteristic Curve (AUC), sensitivity, specificity, accuracy, precision, and F1-score were used as primary indicators to assess model performance. The DeLong test was applied to compare AUC values between the AI model and assessments by senior radiologists.

Timeliness Metrics

AI Processing Time Measurement: The total and average per-case time required for the AI model to perform end-to-end analysis—including image loading, vessel segmentation, feature extraction, and culprit vessel classification—on the test set were recorded. Processing was conducted on a dedicated server equipped with an NVIDIA T4 GPU; model loading time was excluded from the measurement.

Manual Processing Time Measurement: The time required for a radiologist and a radiologic technologist to independently complete the culprit vessel identification task for all test set CTA samples was recorded. Both operators worked in the same environment and used the same software, operating at their typical clinical efficiency. Tasks were performed in divided time blocks to mitigate fatigue-related bias. The total and average times for each operator were obtained.

Collaborative Mode Time Estimation: The average time for the “AI preliminary screening + physician review” workflow was estimated by summing the mean AI processing time and the average physician review time.

Statistical Analysis

All statistical analyses in this study were performed using R software (version 4.1.1, R Foundation for Statistical Computing, Vienna, Austria). For continuous variables, the Kolmogorov-Smirnov test was applied to verify the normality of data distribution. Variables conforming to normal distribution were compared using the independent samples t-test and presented as mean ± standard deviation (SD), while non-normally distributed variables were compared using the Mann-Whitney U test and reported as median (interquartile range, IQR). For categorical variables, between-group comparisons were conducted using the chi-square test or Fisher's exact test, with data presented as count (percentage, %). The intraclass correlation coefficient (ICC) was adopted to evaluate the inter-observer agreement of manual segmentation results between the two radiologists, and an ICC value > 0.75 was defined as good agreement. The DeLong test was used to compare differences in the area under the receiver operating characteristic curve (AUC) values. A two-sided P-value < 0.05 was considered to indicate a statistically significant difference.

Results

Study Population and Baseline Characteristics

A total of 140 patients with hemoptysis were finally enrolled in this study and divided into a training set (n = 101) and a test set (n = 39). For the time-efficiency analysis, 2 cases in the test set were excluded due to the absence of identifiable culprit bleeding vessels; thus, 37 cases were included as evaluable cases. There were no statistically significant differences in baseline characteristics including sex, age, history of alcohol consumption, history of smoking, history of hypertension, and history of infectious diseases between the two groups (all P > 0.05), indicating favorable balance and comparability of baseline data between the two groups (Table 1).

Table 1
Comparison of baseline characteristics between the training set and the test set

Characteristics	Training set (n = 101)	Test set (n = 39)	P value
Sex, n (%)			0.82
Female	33 (32.67)	12 (30.76)	
Male	68 (67.32)	27 (69.23)	
Age (years, mean ± SD)	56 ± 15	55 ± 15	0.88
History of alcohol consumption, n (%)			0.57
No	14 (13.86)	4 (10.25)	
Yes	87 (86.14)	35 (89.74)	
Hypertension, n (%)			0.60
No	73 (72.28)	32 (82.05)	
Yes	28 (27.72)	7 (17.95)	
Infectious disease, n (%)			0.56
No	3 (2.97)	0 (0.00)	
Yes	98 (97.03)	39 (100.00)	

Based on the BA-CTA images of enrolled patients, a total of 300 independent vascular branches were obtained after bronchial artery segmentation and morphological vessel splitting, with a mean of 2.14 branches per patient. All vascular branches were classified with intraoperative DSA findings as the gold standard. Among them, 145 branches (48.33%) were confirmed as hemoptysis culprit vessels by DSA, and 155 branches (51.67%) were non-culprit vessels. The training set included 234 vascular branches (114 culprit vessels, accounting for 48.72%), and the test set included 66 vascular branches (31 culprit vessels, accounting for 46.97%). There was no statistically significant difference in the proportion of culprit vessels between the two groups (P > 0.05), with a balanced distribution of the vascular dataset, which laid a reliable data foundation for subsequent model training and testing.

Performance of the Automated Bronchial Artery Segmentation Model

An automated bronchial artery segmentation model was constructed based on a 3D V-Net network integrating attention mechanism and cascade learning strategy. The core performance metrics of the model in the test set (39 cases) were as follows: the Dice similarity coefficient (DSC) was 0.83 ± 0.21, and the 95% Hausdorff distance (95% HD) was 14.48 mm. The standard deviation of DSC (0.21) indicates variable segmentation performance across cases, especially for small-caliber arteries (< 2 mm) and low-quality images. The typical bronchial artery segmentation results is shown in Fig. 2.

Diagnostic Performance of the Hemoptysis Culprit Vessel Identification Model

Reliability Validation of the Gold Standard for Culprit Vessel Identification

Two senior radiologists with more than 5 years of experience in thoracic vascular imaging diagnosis independently completed the interpretation and annotation of hemoptysis culprit vessels under double-blind conditions for patients' clinical data, intraoperative DSA results, and treatment outcomes. The intraclass correlation coefficient (ICC) of the interpretation results was 0.86 (95% CI: 0.78–0.89), indicating good inter-observer agreement in the interpretation of hemoptysis culprit vessels. The consensus-confirmed interpretation results of culprit vessels could be used as a reliable gold standard for the training and testing of subsequent machine learning models.

Results of Radiomic Feature Selection for Culprit Vessel Identification

Using the "minimum Redundancy Maximum Relevance-Least Absolute Shrinkage and Selection Operator (mRMR-LASSO)" cascade feature selection strategy, 9 optimal features with the highest correlation with hemoptysis culprit vessel identification were finally screened out from 2264 extracted initial radiomic features to construct the classification model, including 3 first-order statistical features and 6 texture features (Table 2).

Table 2
Optimal radiomic features and corresponding coefficients for culprit vessel identification

Features	Coefficients
normalize_glrIm_LongRunEmphasis	0.12
wavelet_firstorder_wavelet-HHH-Range	0.05
log_glszm_log-sigma-4-0-mm-3D-SmallAreaHighGrayLevelEmphasis	0.04
log_glszm_log-sigma-4-0-mm-3D-SmallAreaEmphasis	0.01
log_ngtdm_log-sigma-2-0-mm-3D-Busyness	0.003
wavelet_firstorder_wavelet-LHH-Kurtosis	-0.005
recursivegaussian_glszm_HighGrayLevelZoneEmphasis	-0.01
wavelet_firstorder_wavelet-HLH-Kurtosis	-0.03
discretegaussian_glrIm_LongRunHighGrayLevelEmphasis	-0.03

Performance Comparison of Different Machine Learning Classification Models

Four machine learning classification models, including logistic regression (LR), decision tree, random forest, and support vector machine (SVM), were constructed respectively based on the 9 screened optimal radiomic features. The detailed performance metrics of each model in the training set and test set are shown in Table 3. Among them, the LR model achieved the best comprehensive performance in the test set, with AUC of 0.82 (95% CI: 0.71–0.92), a sensitivity of 0.87, a specificity of 0.69, an accuracy of 0.78, a precision of 0.73, and an F1-score of 0.79. The receiver operating characteristic (ROC) curve, calibration curve, and decision curve analysis of the model are presented in Fig. 3.

Validation of the Clinical Application Value of the End-to-End AI Workflow

Comparison of Diagnostic Efficacy Between the AI Model and Senior Radiologists

In the test set (66 independent vascular branches), the diagnostic efficacy of the optimal LR model for hemoptysis culprit vessel identification was compared with that of two senior radiologists, with the results shown in Table 4. The results of the DeLong test showed that there were no statistically significant differences in AUC between the AI model (0.82, 95% CI: 0.71–0.92) and radiologist A (0.84, 95% CI: 0.74–0.95, P = 0.64), as well as radiologist B (0.82, 95% CI: 0.72–0.93, P = 0.91), indicating that the diagnostic efficacy of the AI model was comparable to that of senior radiologists.

Clinical Time Efficiency Analysis of the AI Workflow

The time consumption of the full workflow for hemoptysis culprit vessel identification was compared between AI and medical staff of different professional levels, with statistical indicators including total time consumption, mean time per case, standard deviation, minimum, maximum, and median values, and the results are shown in Table 5. The results showed that AI alone completed the full workflow analysis of 37 eligible cases in the test set in only 87 minutes, with a mean time of 2.58 minutes per case. Two cases were excluded due to the absence of culprit vessels. In comparison, senior radiologists took 232 minutes to complete the same task, with a mean time of 6.27 minutes per case, while the radiologic technologist group had the longest time consumption, with a total of 603 minutes and a mean time of 16.30 minutes per case.

For the human-machine collaborative modes, the mean time per case of the "AI preliminary screening + radiologist review" mode was 3.56 ± 0.78 minutes, with a total time consumption of 128 minutes; the mean time per case of the "AI preliminary screening + technologist review" mode was 3.62 ± 0.86 minutes, with a total time consumption of 134 minutes. The efficiency comparison revealed that the independent processing efficiency of AI was approximately 2.7-fold higher than that of senior radiologists and 6.9 times higher than that of radiologic technologists.

Table 3
Performance evaluation results of different machine learning models for hemoptysis culprit vessel identification

Model	AUC		Sensitivity		Specificity		Accuracy		Precision		F1-score	
	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test	Training	Test
Decision Tree	0.83 (0.78–0.88)	0.74 (0.62–0.86)	0.72	0.74	0.80	0.62	0.76	0.68	0.80	0.65	0.76	0.69
Logistic Regression	0.83 (0.77–0.88)	0.82 (0.71–0.92)	0.78	0.87	0.75	0.69	0.77	0.78	0.77	0.73	0.78	0.79
Random Forest	0.99 (0.99-1)	0.78 (0.66–0.89)	0.98	0.80	0.98	0.68	0.98	0.74	0.98	0.71	0.98	0.75
Support Vector Machine	0.97 (0.94–0.99)	0.78 (0.66–0.89)	0.97	0.80	0.87	0.62	0.92	0.71	0.89	0.67	0.93	0.73
Note: AUC, area under the receiver operating characteristic curve; values in parentheses are 95% confidence interval (CI).												

Table 4
Comparison of diagnostic efficacy for culprit vessel identification between the AI model and senior radiologists

Evaluation Subject	AUC (95% CI)	Sensitivity	Specificity	Accuracy	P value (vs. AI model)
AI model (Logistic Regression)	0.82 (0.71–0.92)	0.87	0.69	0.78	-
Radiologist A	0.84 (0.74–0.95)	0.87	0.71	0.79	0.64
Radiologist B	0.82 (0.72–0.93)	0.85	0.68	0.77	0.91
Note: AUC, area under the receiver operating characteristic curve; values in parentheses are 95% confidence interval (CI). P values were calculated by the DeLong test, which was performed to compare the differences in AUC between each radiologist and the AI model, with a two-sided test level of $\alpha = 0.05$. Abbreviations: CI, confidence interval; AI, artificial intelligence.					

Table 5
Comparison of time consumption for bronchial artery culprit vessel identification tasks

Indicator	AI	Radiologist	Radiologic Technologist	Radiologist + AI	Technologist + AI
Mean time (min)	2.58 ± 0.60	6.27 ± 1.30	16.30 ± 1.70	3.56 ± 0.78	3.62 ± 0.86
Minimum time (min)	1.6	4	13	3	3
Maximum time (min)	2.9	10	19	6	6
Median time (min)	2.5	6	16	3	3
Total time consumption (min)	87	232	603	128	134
Note: The unit of all time indicators is minute (min). Mean time is presented as mean ± standard deviation. "Radiologist + AI" refers to the human-machine collaborative mode of "AI preliminary screening + radiologist review", and "Technologist + AI" refers to the human-machine collaborative mode of "AI preliminary screening + technologist review". Abbreviations: AI, artificial intelligence.					

Discussion

This study aimed to address the key clinical challenges of time-consuming manual BA segmentation and high subjectivity in the interpretation of hemoptysis culprit vessels, which are difficult to adapt to the needs of emergency diagnosis and treatment. We constructed an end-to-end deep learning pipeline for intelligent BA segmentation and hemoptysis culprit vessel identification based on 3D V-Net. The results of this study confirmed that this pipeline can achieve automated and accurate segmentation of the BA, with diagnostic efficacy for culprit vessel identification comparable to that of senior radiologists. Meanwhile, it can shorten the image post-processing time per case to 2.58 minutes, which greatly improves the efficiency of emergency imaging evaluation for hemoptysis, and verifies the clinical feasibility of deep learning technology to assist the emergency diagnosis and treatment of hemoptysis.

Current studies on automated pulmonary vascular analysis mostly focus on the single vessel segmentation task of pulmonary arteries and pulmonary veins [18–22]. Only a few studies involve automated segmentation and quantitative measurement of bronchial arteries, and most of them focus on the quantitative analysis of bronchial artery diameter and wall thickness for the diagnosis and disease monitoring of bronchiectasis and airway diseases [23, 24]. There is no clinically available scheme for the emergency hemoptysis scenario covering the full workflow of "vessel segmentation - branch splitting - culprit vessel identification", which cannot meet the clinical needs of rapid preoperative evaluation for emergency hemoptysis. The core innovation of this study is that we took the lead in integrating automated BA segmentation and intelligent culprit vessel classification into a set of end-to-end standardized analytical pipeline. In the segmentation task, the 3D V-Net model based on the integration of attention mechanism and cascade learning strategy achieved a DSC of 0.83 ± 0.21 , which is comparable to the performance of existing mature pulmonary vessel segmentation studies, confirming that this network architecture can effectively capture the morphological features of BA with thin diameter and complex anatomical variations. In terms of diagnostic efficacy, the logistic regression model constructed based on radiomic features in this study achieved an AUC of 0.82 for culprit vessel identification, with no statistically significant difference from the diagnostic efficacy of two senior radiologists. This confirms that the model can realize objective and standardized interpretation of culprit vessels and effectively reduce the subjective differences of manual evaluation. Most importantly, the average processing time per case of the pipeline in this study was only 2.58 minutes. Even for the human-machine collaborative mode combined with radiologist review, the time per case could be controlled within 3.56

minutes, which fully meets the time-sensitive requirements of rapid diagnosis and treatment for emergency hemoptysis. This is the core clinical advantage of this study compared with existing similar studies. The identification efficacy of AI for hemoptysis culprit vessels in this study is similar to the research results of Barash et al. in bleeding detection in celiac arteriography, which jointly confirmed that artificial intelligence has stable clinical application value in the accurate identification of vascular hemorrhagic lesions [25]. Kim et al. used 3D deep learning to achieve efficient detection and false positive control of intracranial microbleeds, and its technical idea also provided an important reference for the segmentation of bronchial arteries with thin diameter and high anatomical variation and accurate identification of culprit vessels in this study [26]. Both previous studies support the conclusion that the AI-assisted pipeline in this study can effectively improve the efficiency of imaging evaluation for emergency bleeding, and also expand the application scenarios of artificial intelligence in the diagnosis and treatment of vascular hemorrhagic diseases.

The feature selection results of this study showed that the predictive value of texture features for hemoptysis culprit vessels was significantly better than that of first-order statistical features, which is consistent with the conclusions of radiomic studies on vascular diseases such as coronary artery and pulmonary artery diseases [27–30]. From the perspective of pathophysiological mechanism, hemoptysis culprit vessels mostly have pathological changes such as chronic inflammatory infiltration, vascular wall structural destruction, and microaneurysm formation. These microstructural changes will directly lead to increased gray scale heterogeneity in the vascular region, and texture features can accurately capture such microstructural differences that are difficult to identify by naked eyes [30]. This is the core pathological basis for the radiomic model in this study to achieve accurate identification of culprit vessels. At the same time, this study confirmed that the diagnostic efficacy of the AI model is comparable to that of senior radiologists, with a significant improvement in time efficiency, suggesting that this pipeline can be used as an initial imaging screening tool for emergency hemoptysis, effectively reducing the workload of radiologists. Especially, it can make up for the shortage of insufficient experience in thoracic vascular imaging diagnosis of radiologists in primary hospitals, and has high clinical translational potential [27].

This study has several limitations. First, this is a single-center retrospective study with a relatively small sample size ($n = 140$). There is an uneven distribution of the patient disease spectrum (with a low proportion of lung cancer cases) and insufficient samples of cases with rare anatomical variations of the BA, which may limit the generalization ability of the model. Second, although the reference standard for model training was validated via multi-round expert adjudication, certain subjective annotation differences still exist. Furthermore, no standardized consensus or annotation criteria for BA segmentation and culprit vessel annotation has been established in the field to date. Third, the standard deviation of the DSC of the model segmentation results is relatively large, indicating that there is still potential for performance optimization in the segmentation stability of the model for cases with a vessel diameter < 2 mm and poor image quality. Fourth, the current model inference relies on high-performance GPU hardware, which creates a non-negligible hardware barrier for its widespread clinical implementation in primary hospitals.

In response to the above limitations, subsequent studies will focus on the following work. First, a multi-center, large-sample prospective study will be conducted to expand the sample size, with priority given to supplementing cases of lung cancer, rare anatomical variations of BA, and cases with poor CTA image quality, so as to improve the generalization ability and robustness of the model. Second, we will collaborate with multi-center experts in thoracic imaging and interventional radiology to develop a unified quantitative standard for BA segmentation and culprit vessel annotation, and adopt a double-blind multi-radiologist annotation strategy to reduce the subjective bias of annotation results. Third, the model network architecture will be optimized, with enhanced multi-scale feature fusion and attention mechanism, to improve the segmentation performance of the model for fine-caliber vessels and low-quality images. Fourth, model quantization and lightweight technology will be applied to reduce the hardware dependence of the model and improve its deployment feasibility in primary medical settings. Fifth, prospective validation in a real-world clinical emergency setting will be performed to systematically evaluate the actual impact of this pipeline on the diagnosis and treatment outcomes and length of hospital stay of patients with hemoptysis, to further verify its clinical value.

Conclusion

In conclusion, we developed and validated an end-to-end deep learning pipeline for fully automated bronchial artery segmentation and intelligent identification of culprit hemoptysis vessels. This pipeline achieves high segmentation accuracy and diagnostic performance comparable to senior radiologists while drastically reducing processing time. It addresses the key limitations of conventional manual methods including high subjectivity, low efficiency, and lack of standardization. This automated workflow represents a promising auxiliary tool for emergency hemoptysis evaluation and precise preoperative planning for bronchial artery embolization, with high clinical feasibility and translation potential.

Abbreviations

BA: Bronchial artery

BAE: Bronchial artery embolization

CTA: Computed tomography angiography

DSA: Digital subtraction angiography

DSC: Dice similarity coefficient

HD: Hausdorff distance

AUC: Area under the curve

ICC: Intraclass correlation coefficient

mRMR: Minimum Redundancy Maximum Relevance

LASSO: Least Absolute Shrinkage and Selection Operator

LR: Logistic regression

SVM: Support vector machine

AI: Artificial intelligence

ROI: Region of interest

3D: Three-dimensional

HU: Hounsfield Unit

Declarations

Ethics approval and consent to participate

This study was conducted in strict accordance with the ethical principles of the Declaration of Helsinki and its later amendments. The study protocol was approved by the Ethics Committee of the People's Hospital of Xiangxi Tujia and Miao Autonomous Prefecture (Ethics Approval No. XXZRY-LCKY-2025-71). Due to the retrospective nature of this study, all clinical and imaging data were fully anonymized. The Ethics Committee waived the requirement for written informed consent from all participants. No study-related interventional examinations or treatments were performed on the subjects, and all imaging examinations and therapeutic regimens were part of routine clinical practice.

Consent for publication

Not applicable. This study does not contain any identifiable personal images, details, or private information from individual participants.

Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available due to patient privacy protection and institutional data management regulations, but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Jicheng Jiang contributed to study design, data collection, image annotation, model construction, original draft writing, and figure and table preparation. Qiang Liu performed statistical analysis and data processing. Hong Deng, Yingjuan Wu, Yunrong Zhao, and Li'an Luo provided academic guidance and revised the manuscript critically for important intellectual content. All authors participated in the revision of the manuscript. All authors have read and approved the final version to be published.

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Figures

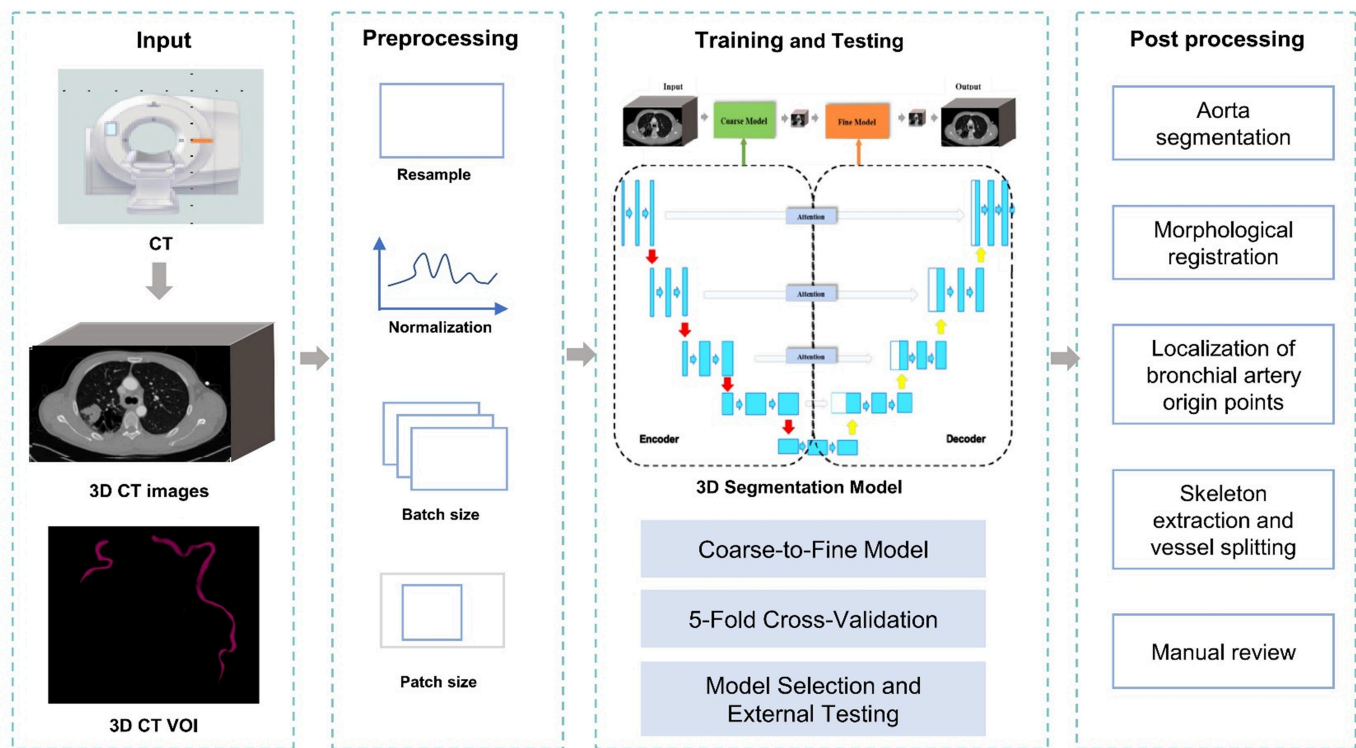


Figure 1

Flowchart of Bronchial Artery Segmentation and Branch Splitting

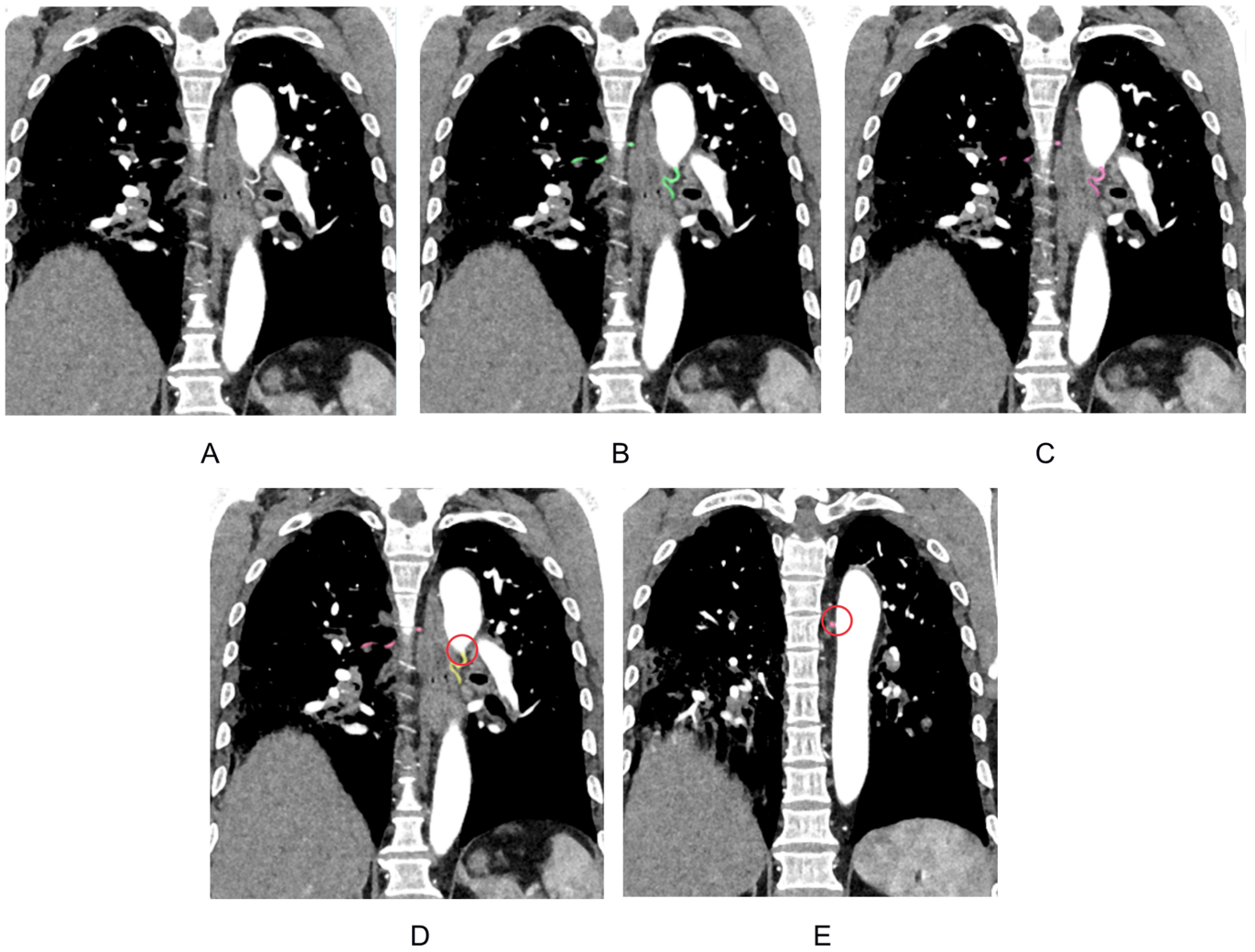


Figure 2

Representative images of bronchial artery segmentation results. (A) Original CTA image; (B) Bronchial artery map manually delineated by radiologists; (C) Automatic segmentation result output by the model algorithm; (D) Individual bronchial branches after vessel splitting. The red boxed areas (D and E) indicate the origin of the bronchial artery.

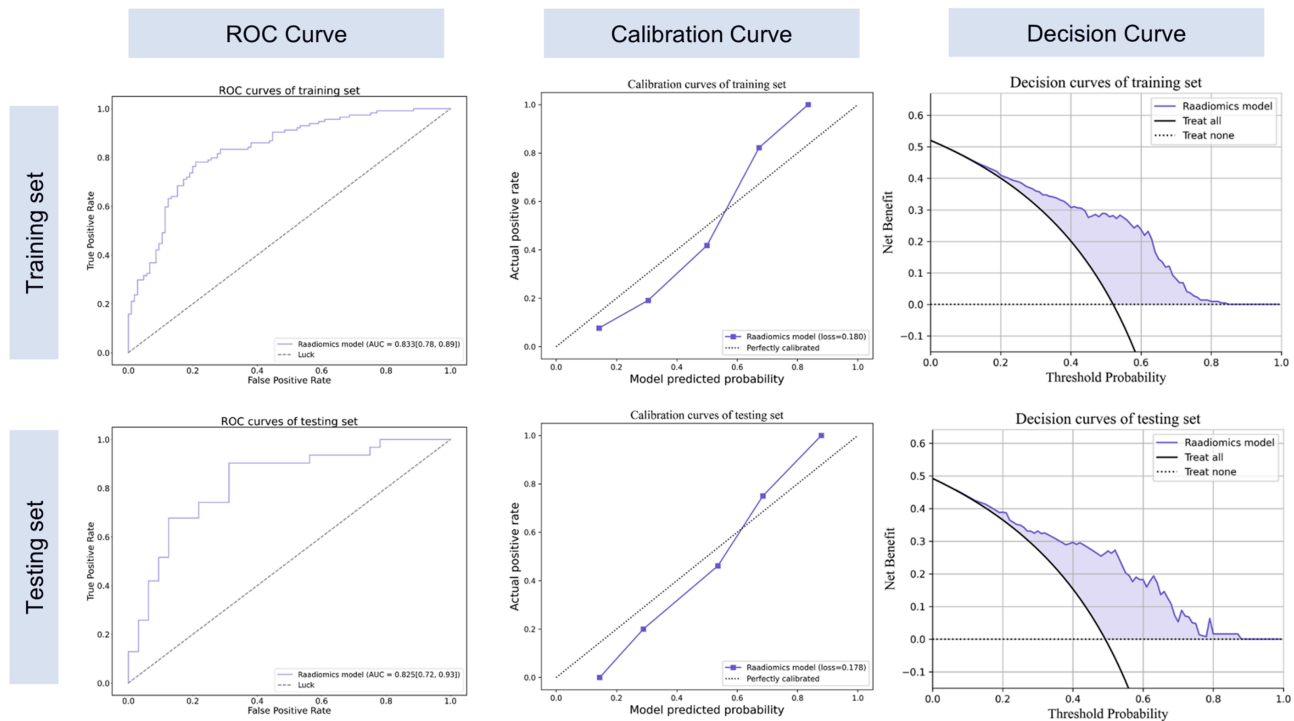


Figure 3

Receiver operating characteristic (ROC) curves, calibration curves, and decision curves of the radiomic model in the training set and test set.