

CT-based Deep Learning Radiomics Analysis for Predicting Postoperative Pancreatic Fistula after Pancreatectomy

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Research Article

Keywords: deep learning, radiomics, pancreatic fistula, combined model

Posted Date: October 27th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10887227/v1>

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Additional Declarations: No competing interests reported.

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Abstract

Background: Clinically relevant postoperative pancreatic fistula (CR-POPF) is a severe complication following pancreatic surgery. However, the preoperative prediction of CR-POPF remains challenging. This study aims to develop and validate a deep learning radiomics (DLR) model that integrates imaging and clinical features for CR-POPF prediction.

Methods: This retrospective study included 425 patients who underwent pancreatic surgery between January 2020 and April 2024. Then, preoperative contrast-enhanced computed tomography (CT) images and clinical data were collected. Afterwards, the radiomics features were extracted from the CT images, and deep learning features were obtained using ResNet50. Subsequently, these features were integrated into a DLR model, and feature selection was performed *via* LASSO regression, yielding seven key features. Then, a clinical model was developed using univariate and multivariable logistic regression. The combined model integrated the DLR and clinical models. Model performance was evaluated using receiver operating characteristic (ROC) curves, calibration curves, and decision curve analysis (DCA). The DeLong test was used to compare the area under the receiver operating characteristic curves (AUCs).

Results: The overall incidence of CR-POPF was 19.76%. The DLR model, which integrated the radiomics and deep learning features, outperformed the clinical model and radiomics-only model. In the test cohort, the combined model achieved an AUC of 0.819 (95% CI: 0.732-0.906), outperforming the clinical model (AUC: 0.767) and DLR model (AUC: 0.803). The calibration and DCA confirmed the superior clinical utility of the combined model, with higher net benefits at various risk thresholds.

Conclusions: The combined DLR model that integrated imaging features and clinical variables demonstrated superior performance in preoperatively predicting CR-POPF. This approach provides a promising tool for personalized risk assessment in pancreatic surgery.

Keywords: deep learning; radiomics; pancreatic fistula; combined model

Introduction

Pancreatectomy is a complex and high-risk procedure¹. Among the various complications, postoperative pancreatic fistula (POPF) is the most concerning due to its high incidence and associated mortality². POPF significantly increases surgery-related mortality and adversely affects patient prognosis, with reported incidence rates reaching as high as 30% in high-volume centers^{3,4}.

In 2016, the International Study Group of Pancreatic Fistula (ISGPF) revised the diagnostic and grading criteria for POPF, classifying grade B and C pancreatic fistulas as clinically relevant postoperative pancreatic fistula (CR-POPF)⁵. CR-POPF is characterized not only by the elevated amylase levels in abdominal drainage fluid, but also by the changes in clinical management and patient outcomes⁶. Thus, the early and accurate identification of CR-POPF is critical for timely therapeutic intervention, potentially preventing complications, such as multiple organ failure, severe bleeding, and death⁷.

The Pancreatic Fistula Risk Score (FRS) and the Alternative Pancreatic Fistula Risk Score (A-FRS) are commonly used for assessing the risk of CR-POPF. However, both are primarily based on intraoperative factors, which limits its applicability for preoperative risk evaluation^{8,9}. Approximately 50% of patients fall into the moderate-risk “gray zone”,⁸ and the subjective nature of intraoperative pancreatic texture assessment--due to inconsistent criteria among operators--further complicates risk prediction¹⁰. Therefore, there is a clear need for a preoperative risk stratification model that incorporates objective, reproducible variables to improve clinical decision-making.

Conventional non-invasive preoperative pancreatic assessment methods, such as computed tomography (CT)-based risk stratification, relies on macroscopic parameters, which fail to capture the parenchymal microheterogeneity predictive of CR-POPF. Radiomics features derived from the pancreatic parenchyma, including shape-based and textural

characteristics¹¹, may reflect the extent of pancreatic fibrosis, ductal dilatation, pancreatic texture, and tissue distribution--all factors associated with CR-POPF¹². These features can be extracted through computer-assisted image analysis, and deep learning algorithms further enhance the accuracy and efficiency of radiomics, enabling the identification of subtle image patterns that were previously undetectable¹³.

The objective of the present study was to develop a deep learning-based radiomics model to predict CR-POPF, with the goal of identifying the early changes in pancreatic tissue, and providing early warning information for both patients and clinicians.

Materials and Methods

Study Design and Ethics Approval

The complete procedure of the study is shown in Figure 1. The present retrospective, single-center study was conducted at Chongqing General Hospital, which has a high surgical volume for pancreatic disease. The institutional review board approved the study protocol, and waived the requirement for informed consent due to the retrospective design and minimal risk to patients. All research procedures adhered to the principles of the Declaration of Helsinki. The approval number is IIT S2025-046-01.

Patient Selection

Patients who underwent elective pancreatic surgery between January 2020 and April 2024 were consecutively screened. The inclusion criteria were, as follows:

- (1) Acceptance of standard surgical procedures and unified standard postoperative care and rehabilitation treatment performed by the same expert team, with consistent basic surgical procedures and postoperative abdominal retention of the luminal drainage tube;
- (2) Availability of preoperative contrast-enhanced CT performed within two weeks before

surgery;

(3) Complete clinical, surgical, and postoperative follow-up data.

The exclusion criteria were, as follows:

(1) Prior pancreatic surgery or neoadjuvant therapy;

(2) Poor-quality CT images or incomplete contrast enhancement;

(3) Missing key postoperative outcome data.

A total of 425 patients satisfied all criteria, and were included in the model development and validation. Patients were randomly assigned to the training (70%) and internal validation (30%) cohorts using stratified sampling based on CR-POPF incidence (Supplementary A1).

CT Image and Region of Interest (ROI) Segmentation

All patients underwent abdominal multiphase contrast-enhanced CT using 64 detector row scanners before surgery. The details of the CT scan protocols are depicted in Supplementary A2. The portal venous phase was selected for radiomics and deep-learning analysis due to optimal parenchymal enhancement.

Prior to the analysis, the images underwent preprocessing, which included resampling of the voxel size and discretizing of the Hounsfield Units. In order to address the voxel resolution discrepancies that resulted from the acquisition process, the voxel dimensions were resampled to $1 \times 1 \times 1$ mm along the x, y, and z axes.

Manual segmentation of the pancreatic remnant was performed on the portal venous phase images using ITK-SNAP (version 3.8.0). Two radiologists with eight and 15 years of abdominal imaging experience, respectively, independently segmented all cases. Any discrepancies were adjudicated through consensus with a senior radiologist to ensure segmentation accuracy and reproducibility.

Radiomics Procedure

Feature Extraction

The handcrafted radiomic features were extracted from each ROI using the ITK toolkit (version 3.8). Before extraction, the image intensities were discretized, and wavelet decomposition was applied to generate eight frequency sub-bands (HLL, HLH, HHH, HHL, LHH, LHL, LLH and LLL), enabling multi-scale characterization. The features were calculated from both the original and wavelet-transformed images, yielding 850 radiomic features across four categories: (1) shape features ($n=13$): quantified the three-dimensional pancreatic geometry; (2) first-order features ($n=18$): summarized the voxel intensity distributions within the ROI; (3) texture features ($n=75$): captured the spatial gray-level patterns using gray-level co-occurrence matrix (GLCM), gray-level run length matrix (GLRLM), grey-level size zone matrix (GLSZM), gray-level difference method (GLDM), and neighborhood gray-tone difference matrix (NGTDM) matrices; (4) wavelet features ($n=744$): represented fine-to-coarse spatial and frequency variations across all wavelet sub-bands.

Feature Selection

In order to ensure feature stability against segmentation variability, the robustness of the imaging features were initially assessed. Test-retest and inter-rater analyses were performed using two independent datasets (each $n=30$). In the test-retest set, each tumor subregion was contoured twice by the same rater. In the inter-rater set, two raters independently segmented each case. Features extracted from these repeated segmentations were evaluated using the intraclass correlation coefficient (ICC), and those with $ICC \geq 0.85$ were retained.

In order to further reduce redundancy, pairwise Spearman correlation coefficients were computed. For any feature pair with correlation ≥ 0.90 , one feature was discarded. Ultimately,

150 features remained, representing a compact set of robust, predictive, and minimally redundant imaging descriptors.

Model Construction

Employing the logistic least absolute shrinkage and selection operator (LASSO) for rigorous feature selection, the radiomics risk model was constructed using machine learning algorithms, such as Logistic Regression, Support Vector Machine, and Random Forest. Then, comparative analyses were conducted to evaluate the performance of each model, and the benefits of the feature fusion were investigated by integrating multi-modal features, allowing the investigators to explore the advantages of combining multiple imaging modalities to enhance predictive accuracy.

Deep Learning Procedure

Data Preparation

Crop ROI: In the methodology of the investigators, for each patient, the slice that presented the largest ROI was selected as the representative image. In order to reduce complexity and minimize background noise in the present algorithmic analysis, merely the smallest bounding rectangle that encompassed the ROI was retained. The rectangle was expanded by an additional 10 pixels.

Data Augmentation: The present approach involved standardizing the intensity distribution across the RGB channels by normalizing the images using Z-score normalization. Then, these normalized images were utilized as inputs for the present model. During the training phase, real-time data augmentation strategies were implemented, which included random cropping, horizontal flipping, and vertical flipping. For the test images, processing was restricted to normalization only.

Deep Learning Feature Extraction

For each patient, the CT slice with the largest ROI was cropped and normalized using z-score standardization. Then, a ResNet-50 convolutional neural network pre-trained on ImageNet was fine-tuned on the pancreatic CT data. Afterwards, the outputs of the penultimate layer was extracted as deep-learning features (2,048 dimensions), which were reduced to 512 dimensions *via* principal component analysis for integration with radiomic features.

Model Training

Transfer Learning: In the present study, the performance of prominent networks, including ResNet50, was explored to enhance the performance of traditional CNN-based models. In addition, the comparative analysis of these models was conducted to identify the most suitable algorithm for the specific research requirements of the present study.

Hyper Parameters: In the present study, in order to ensure the model's effectiveness across various patient populations with significant variability, transfer learning was implemented. The process involved initializing the model with pre-trained weights from the ImageNet database to enhance its adaptability to diverse datasets. The critical aspect of the present approach involved the meticulous adjustment of the learning rate to enhance generalization across datasets. To this end, the cosine decay learning rate strategy was utilized, which was defined, as follows:

$$\eta_t = \eta_{min}^i + \frac{1}{2}(\eta_{max}^i - \eta_{min}^i)(1 + \cos(\frac{T_{cur}}{T_i}\pi))$$

The notation $\eta_{min}^i = 0$ sets the minimum learning rate, while $\eta_{max}^i = 0.01$ establishes the maximum learning rate. The term $T_i = 30$ denotes the number of epochs in the iterative training process. Other essential hyperparameters

included the use of Stochastic Gradient Descent (SGD) as the optimizer and softmax cross-entropy for the loss function.

Feature Early Fusion: The $features_{ct}$, $features_{dwi}$ was integrated using a feature concatenation method ($\oplus$), combining these into a single comprehensive feature vector:

$$feature_{fusion} = features_{ct} \oplus features_{dwi}$$

Deep Learning Radiomics (DLR) Signature Construction

The DLR signature was constructed using a pre-fusion algorithm that integrated deep-learning and selected radiomic features. The feature selection and model construction followed the radiomics workflow, including statistical filtering, correlation analysis, and LASSO regression with 5-fold cross-validation, in order to retain the most predictive features.

Combined Model

Clinical variables were screened using univariable logistic regression, followed by stepwise multivariable analysis to identify the independent predictors. Then, these clinical features were combined with the DLR signature in a logistic regression framework to form the Combined Signature, which was visualized as a nomogram for individualized CR-POPF risk estimation.

Model Evaluation

Discriminative performance was assessed *via* receiver operating characteristic (ROC) curves, with the area under the receiver operating characteristic curve (AUC) as the primary metric. Calibration was evaluated using calibration plots and the Hosmer-Lemeshow test.

Clinical utility was quantified using Decision Curve Analysis (DCA) to determine the net benefit across varying risk thresholds.

Statistical Analysis

The normality of continuous clinical variables was assessed using the Shapiro-Wilk test. Depending on the distribution, continuous variables were compared using Student's *t*-test or Mann-Whitney U test, while categorical variables were analyzed using Chi-square (χ^2) test. The baseline characteristics for all cohorts are summarized in Table 1. A p-value of >0.05 indicated no significant differences, confirming the unbiased cohort allocation.

All data analyses were executed on the OnekeyAI platform, version 4.9.1, utilizing Python 3.7.12. Statistical assessments were conducted with Statsmodels, version 0.13.2. Radiomics feature extraction was performed *via* PyRadiomics, version 3.0.1. Machine learning implementations, including the Support Vector Machine (SVM), were facilitated using Scikit-learn, version 1.0.2. The deep learning frameworks employed for the present study were developed on PyTorch, version 1.11.0.

The analyses in the present study were conducted using Python version 3.7.12 and statsmodels version 0.13.2. The development of the present machine learning models utilized the scikit-learn version 1.0.2 interface. For deep learning training, the NVIDIA 4090 GPU, with MONAI version 0.8.1 and PyTorch version 1.8.1 frameworks, was employed.

Results

Patient Characteristics

A total of 425 consecutive patients were included, which comprised of 341 patients in the non-CR-POPF group and 84 patients in the CR-POPF group, yielding a CR-POPF incidence of 19.76%. Compared with the non-CR-POPF group, patients who developed CR-POPF

exhibited higher body mass index (BMI) (23.8 vs. 22.0, $p=0.002$) and C-reactive protein (CRP) (47.2 vs. 41.2 mg/L, $p=0.017$) levels, lower carbohydrate antigen 19-9 (CA19-9) values (12.4 vs. 37.3 U/mL, $p=0.001$), reduced intraoperative blood loss (100 vs. 200 mL, $p=0.010$), smaller pancreatic duct diameter (PDD) (0.20 vs. 0.30 cm, $p<0.001$), and lower PDCTv-r (2.42 vs. 2.74, $p<0.001$) and DPCTv-r (1.97 vs. 2.25, $p<0.001$). Furthermore, statistically significant differences were observed in lesion position ($p=0.002$) and surgery type ($p=0.006$). No significant differences were noted for sex, age, diabetes history, prior pancreatitis, preoperative chemotherapy, serum albumin, total bilirubin (TBIL), or APVTv-r (Table 1).

The univariable analysis of clinical features identified several factors associated with CR-POPF. Features significant in the univariate screening were further considered for constructing the Clinical Signature. The multivariable logistic regression revealed that PDD (OR = 0.14, 95% CI: 0.04-0.49, $p=0.002$), CRP (OR = 1.01, 95% CI: 1.00-1.01, $p<0.001$), and DPCTv-r (OR = 0.35, 95% CI: 0.19-0.62, $p<0.001$) were independent predictors of CR-POPF (Table 2).

Model Performance and Interpretability

Gradient-weighted Class Activation Mapping (Grad-CAM) Visualization

In order to interpret the deep learning model's decision-making, Grad-CAM was applied. As shown in Figure 2, Grad-CAM highlighted the regions within the pancreas that contributed most to the CR-POPF predictions, providing insight into the spatial areas that influenced the model outputs, and enhancing interpretability.

Performance and Comparison of Models

The combined model, which integrated the DLR signature with key clinical variables, consistently outperformed both the clinical-only and DLR-only models across the training

and test cohorts. In the training cohort, the combined model achieved an AUC of 0.836 (95% CI: 0.786-0.887), while in the test cohort, the combined model achieved an AUC of 0.819 (95% CI: 0.732-0.906) (Table 3). Furthermore, the ROC curves demonstrated superior discriminative ability of the combined model, while the calibration plots confirmed the good agreement between the predicted and observed outcomes, with the combined model showing the best calibration (Figure 3). The calibration curves of the three models are shown in Figure 4. It can be observed that the combined model was better than the other two models.

The DCA indicated that the combined model provided greater net clinical benefit across relevant risk thresholds, when compared with the clinical or DLR models alone (Figure 5). For practical application, the combined model was visualized as a nomogram to facilitate the individualized preoperative CR-POPF risk assessment (Figure 6).

The statistical comparison using the DeLong test confirmed that the AUC of the combined model was significantly higher than that of the clinical model ($p=0.001$). Furthermore, the Net Reclassification Improvement (NRI) and Integrated Discrimination Improvement (IDI) analyses demonstrated that the combined model significantly enhanced predictive accuracy and patient risk stratification relative to both the clinical and DLR-only models (Figure 7).

Discussion

CR-POPF remains a significant and challenging complication following pancreatectomy. Certain reported prediction models have proposed robust CR-POPF prediction frameworks within well-defined clinical scenarios, demonstrating satisfactory discriminatory performance through the comprehensive assessment of perioperative risk factors¹³⁻¹⁵. However, some critical variables, such as intraoperative pancreatic texture palpation, can only be subjectively evaluated during or after surgical procedures. The inter-operator variability in tactile

assessments of pancreatic consistency often leads to the inconsistent interpretation of predictive values, thereby compromising the reliability and validity of model outputs. This inherent lack of standardized evaluation criteria suggests that existing methodologies may suffer from insufficient reproducibility and objectivity, potentially impeding its widespread clinical translation and practical implementation.

Multiple studies have demonstrated that preoperative CT measurements, including PDD, are independently associated with CR-POPF¹⁶. In the present cohort, the maximum PDD measured on preoperative CT scans was identified as an independent predictor of CR-POPF. The increased risk associated with a smaller duct is multifactorial. Technically, performing a pancreaticoenterostomy on a narrow main pancreatic duct (MPD) is more challenging than on a dilated duct, and reduced duct size may impair postoperative pancreatic juice drainage¹⁷. These findings are consistent with previous reports, reinforcing the clinical relevance of pancreatic duct assessment for preoperative risk stratification.

CRP, which is the primary acute-phase reactant synthesized by the liver with a half-life of approximately 19 hours, exhibits a rapid and predictable response to surgical stress. Serum CRP levels rise within six hours postoperatively, peaking at approximately 48 hours¹⁸. In uncomplicated recovery, CRP gradually declines over the subsequent days, while in patients who develop complications, such as CR-POPF, CRP remains elevated, reflecting ongoing systemic inflammation. Consistent with prior studies^{18,19}, the present analysis demonstrated significantly higher postoperative CRP levels in the CR-POPF cohort, when compared with the non-CR-POPF group. These findings underscore CRP as an independent prognostic biomarker, highlighting its potential utility for early risk stratification and targeted postoperative management.

Pancreatic firmness, which reflects the degree of parenchymal fibrosis, is a well-recognized risk factor for CR-POPF. Dynamic contrast-enhanced magnetic resonance

imaging (MRI) has been shown to effectively assess pancreatic fibrosis and predict CR-POPF. For example, Shi *et al.*²⁰ used MRI elastography to quantify tissue stiffness, suggesting its potential as a preoperative predictive biomarker. However, MRI is costly and time-consuming, limiting its routine clinical application in the preoperative non-invasive prediction of CR-POPF. Previous studies have established that shear wave elastography (SWE) can effectively evaluate tissue fibrosis. Therefore, utilizing Virtual Touch IQ (VTIQ) technology to quantitatively assess pancreatic parenchymal fibrosis and predict CR-POPF risk preoperatively may represent as a viable and promising approach^{21,22}. Kuwahara *et al.*²³ used endoscopic ultrasound elastography to assess pancreatic parenchymal stiffness and predict the occurrence of CR-POPF. Their findings indicated a significant correlation between the average pancreatic elasticity value and the incidence of CR-POPF. However, endoscopic ultrasonography is a relatively invasive procedure, and the examination process is quite complex. At present, few studies have attempted to use CT values to predict CR-POPF. CT values are simple and non-invasive to obtain, and the present measurement method can effectively prevent the impact of local tumor tissue infiltration and the supportive effect of dilating the main pancreatic duct on pancreatic softness and hardness. The present results indicated that the DPCTv-r (ratio of delayed CT values to plain CT values) in the CR-POPF group is lower than that in the non-CR-POPF group, which may indirectly suggest that a pancreas with a softer texture is more prone to pancreatic fistula.

Compared to traditional radiomics²⁴, deep learning models can overcome the complexity and subjectivity of manual lesion segmentation, thereby improving both analytical efficiency and predictive accuracy²⁵. Although previous studies have applied deep learning or radiomics individually for CR-POPF prediction, few studies have explored the combined integration of these modalities^{12,13,26}. In the present study, a DLR model that fused enhanced CT-derived deep learning features with key clinical variables was developed and validated. The present

findings demonstrated that the combined model outperforms the clinical-only model, offering superior predictive accuracy and enhanced clinical utility for preoperative CR-POPF risk stratification.

Several inherent limitations of the present study should be recognized. First, its single-center, retrospective design may have introduced selection bias, potentially limiting the generalizability of the present findings. Secondly, the PDD in the present model was derived from the maximum measurement on CT, which may not accurately represent the actual caliber at the anastomotic site, potentially affecting predictive precision. Third, the relatively small sample size precluded the subgroup analyses for patients with grade B or C POPF, necessitating the cautious interpretation of results within these subsets. Future studies would aim to address these limitations by expanding the cohort, and validating the model performance in diverse, multi-center populations.

Conclusion

The synergistic integration of deep learning algorithms, radiomics features, PDD, C-reactive protein, and DPCTv-r for the preoperative prediction of CR-POPF was systematically investigated. Based on these multifaceted factors, a novel predictive model that outperform standalone deep learning or traditional clinical models was developed. Nonetheless, its generalizability and robustness require validation in larger, prospective cohorts. Future work would focus on integrating this framework into radiology information systems and surgical navigation platforms, facilitating personalized surgical planning, and optimizing perioperative management through improved preoperative risk stratification, intraoperative decision-making, and postoperative monitoring.

Declarations

Abbreviations

AUC	area under the receiver operating characteristic curve
CI	confidence interval
NRI	Net Reclassification Improvement
IDI	Integrated Discrimination Improvement
ICC	intraclass correlation coefficient
ROI	regions of interest
DCA	decision curve analysis

Ethics approval and consent to participate

The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki and its subsequent amendments. This study was approved by the ethics committee of Chongqing General Hospital (IIT S2025-046-01).

Consent for publication

Not Applicable

Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available because the subjects did not provide written consent for their data to be publicly shared. However, datasets can be obtained by request from Lili Liu (liulili007@163.com).

Competing interests

The authors declare that they have no competing interests.

Funding

This study has received funding by the Chongqing Municipal Science and Health Joint Medical Research Project (No.2026MSXM147).

Authors Contributions

Lili Liu: Conceptualization, Methodology, Formal analysis, Data curation, Writing-original draft, Writing-review and editing;

Shaoquan Zhou: Investigation, Data curation, Conceptualization, Software, Methodology;

Xiong Ran: Methodology, Data Curation

Meiling Gong: Methodology, Data Curation;

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Acknowledgements

We thank for the support from the Chongqing Municipal Science and Health Joint Medical Research Project (No.2026MSXM147).

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Table legends

Table1 Comparison of Baseline Characteristics in Patients With and Without CR-POPF

Characteristics	Non-CR-POPF (n=341)	CR-POPF (n=84)	<i>P</i> value
Gender			0.759
Femal	155 (45.5%)	36 (42.9%)	
Male	186 (54.5%)	48 (57.1%)	
Age (years)	58.0 [50.0, 67.0]	56.0 [47.0, 64.2]	0.244
Position			0.002
0	251 (73.6%)	47 (56.0%)	
1	90 (26.4%)	37 (44.0%)	
Diabetes			0.471
No	261 (76.5%)	68 (81.0%)	
Yes	80 (23.5%)	16 (19.0%)	
Pancreatitis			1.000
No	321 (94.1%)	79 (94.0%)	
Yes	20 (5.87%)	5 (5.95%)	
CA-199 (u/ml)	37.3 [9.3, 225]	12.4 [5.62, 85.9]	0.001
ALB	40.6 [37.6, 43.4]	41.6 [38.5, 44.5]	0.774
TBIL	12.5 [8.1, 39.2]	12.8 [8.85, 21.8]	0.659
PCH			0.659
No	297 (87.1%)	71 (84.5%)	
Yes	44 (12.9%)	13 (15.5%)	

Surgery type			0.006
0	76 (22.3%)	21 (25.0%)	
1	168 (49.3%)	26 (31.0%)	
2	97 (28.4%)	37 (44.0%)	
Blood loss (ml)	200 [100, 300]	100 [100, 200]	0.010
CRP	41.2 [27.8, 63.0]	47.1 [31.3, 82.5]	0.017
PDD	0.30 [0.20, 0.60]	0.20 [0.10, 0.30]	<0.001
BMI	22.0 [20.0, 24.5]	23.8 [21.2, 25.0]	0.002
APCTv-r	2.53 [2.14, 2.93]	2.47 [2.17, 2.71]	0.299
PDCTv-r	2.74 [2.33, 3.33]	2.42 [2.19, 2.81]	<0.001
DPCTv-r	2.25 [1.94, 2.81]	1.97 [1.74, 2.27]	<0.001

Table 1. Comparison of Baseline Characteristics in Patients with and without CR-POPF.

ALB, serum albumin; TBIL, total bilirubin; CRP, C-reactive protein; PDD, pancreatic duct diameter; BMI, body mass index; PCH, preoperative chemotherapy history. Surgery type: 0 corresponds to the pancreatic neck resection (surgical excision of the pancreatic neck segment); 1 represents the pancreaticoduodenectomy (Whipple procedure), including both classic pancreaticoduodenectomy and duodenum-preserving variants; 2 signifies the distal pancreatectomy (tail pancreatectomy involving the resection of the pancreatic body and tail). Position 0, the head and neck of the pancreas, duodenum and Ampulla of Vater; Position 1, the body and tail of the pancreas; APCTv-r, the ratio of pancreatic arterial phase computed tomography (CT) values to plain CT values outside the resection site; PDCTv-r, the ratio of pancreatic portal phase CT values to plain CT values outside the resection site; DPCTv-r, the

ratio of pancreatic delayed phase CT values to plain CT values outside the resection site.

Table 2. Univariable and Multivariate Analysis of clinical features.

Table 2 Univariable and Multivariate Analysis of clinical features.				
feature_name	Univariate analysis	p_value	Multivariate analysis	p_value
	OR (95% CI)		OR (95%CI)	
PDD	0.07 (0.02-0.23)	<0.01	0.15 (0.04-0.53)	0.004
Diabetes	0.77 (0.42-1.40)	0.387		
Pancreatitis	1.02 (0.37-2.79)	0.976		
PCH	1.24 (0.63-2.42)	0.536		
Gender	1.11 (0.69-1.80)	0.668		
Position	2.20 (1.34-3.60)	0.002	1.66 (0.60-4.61)	0.332
Surgtype	0.56 (0.30-1.06)	0.074		
Pancreatic texture	0.59 (0.36-0.95)	0.030	0.69 (0.40-1.17)	0.167
DPCTv-r	0.25 (0.14-0.44)	<0.01	0.33 (0.11-0.93)	0.037
APCTv-r	0.77 (0.53-1.13)	0.184		0.321
PDCTv-r	0.41 (0.27-0.63)	<0.01	1.10 (0.50-2.42)	0.822
path	1.05 (0.91-1.22)	0.487		
BMI	1.12 (1.04-1.21)	0.004	1.08 (0.99-1.17)	0.099

feature_name	Univariate analysis	p_value	Multivariate analysis	p_value
	OR (95% CI)		OR (95%CI)	
Alb	1.06 (1.00-1.13)	0.034	1.01 (0.95-1.08)	0.716
Age	0.99 (0.97-1.01)	0.268		
TBIL	1.00 (0.99-1.00)	0.040	1.00 (0.99-1.00)	0.448
CRP	1.01 (1.00-1.01)	<0.01	1.01 (1.00-1.01)	<0.01
Blood loss	1.00 (1.00-1.00)	0.550		
CA_199	1.00 (1.00-1.00)	0.112		

Notes: OR, odds ratio; CI, confidence interval; ALB, serum albumin; TBIL, total bilirubin; CRP, C-reactive protein; PDD, pancreatic duct diameter; BMI, body mass index. Surgery type: 0 corresponds to pancreatic neck resection (surgical excision of the pancreatic neck segment); 1 represents the pancreaticoduodenectomy (Whipple procedure), including both classic pancreaticoduodenectomy and duodenum-preserving variants; 2 signifies the distal pancreatectomy (tail pancreatectomy involving the resection of the pancreatic body and tail). Position 0, the head and neck of the pancreas, duodenum, and Ampulla of Vater; Position 1, the body and tail of the pancreas; APCTv-r, the ratio of pancreatic arterial phase computed tomography (CT) values to plain CT values outside the resection site; PDCTv-r, the ratio of pancreatic portal phase CT values to plain CT values outside the resection site; DPCTv-r, the ratio of pancreatic delayed phase CT values to plain CT values outside the resection site.

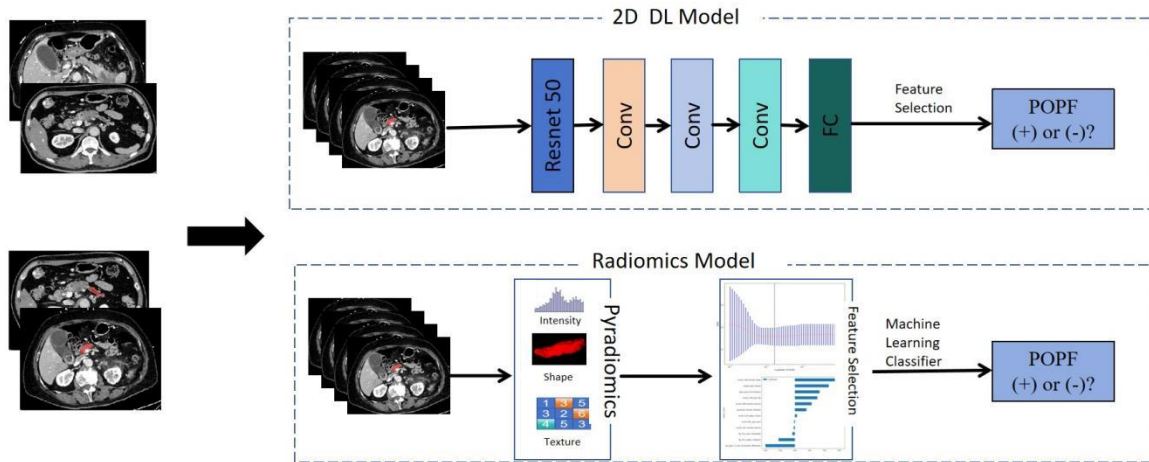
Table 3. Performances of Various Predictive Models in the Training and Test Cohorts.

Table 3 Performances of Various Predictive Models in Training and Test Cohorts								
Signature	Accuracy	AUC	95% CI	Sensitivity	Specificity	PPV	NPV	Cohort
Clinic	0.707	0.743	0.679- 0.807	0.726	0.702	0.391	0.907	train
DLR	0.704	0.808	0.755 - 0.861	0.855	0.664	0.402	0.945	train
Combined	0.761	0.836	0.786 - 0.887	0.903	0.723	0.463	0.966	train
Clinic	0.875	0.795	0.684 - 0.906	0.636	0.925	0.636	0.925	test
DLR	0.641	0.750	0.638 - 0.861	0.864	0.594	0.306	0.955	test
Combined	0.750	0.819	0.732 - 0.906	0.864	0.726	0.396	0.962	test

AUC, area under receiver operating characteristic curve; ROC curve, receiver operating characteristic curve; ACC, accuracy; CI, confidence interval

Setp 1 Tumor Segmentation

Setp 2 Model Construction



Step 3 Stacking Model Construction and Model Evaluation

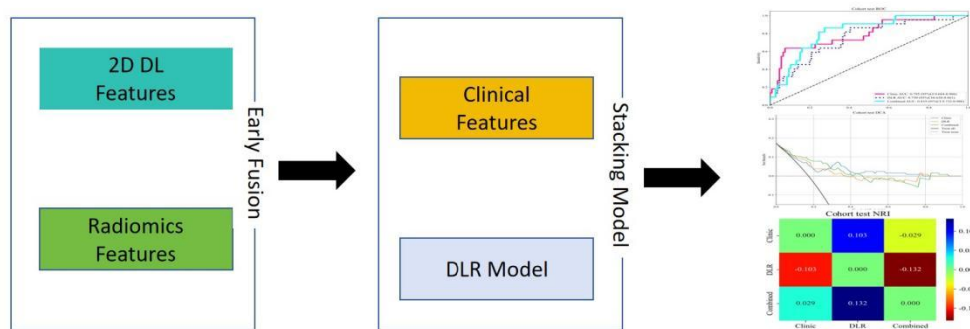


Figure 1 The procedure of the present study.

Notes: 2D, two-dimensional; DL, deep learning; DLR, deep learning radiomics

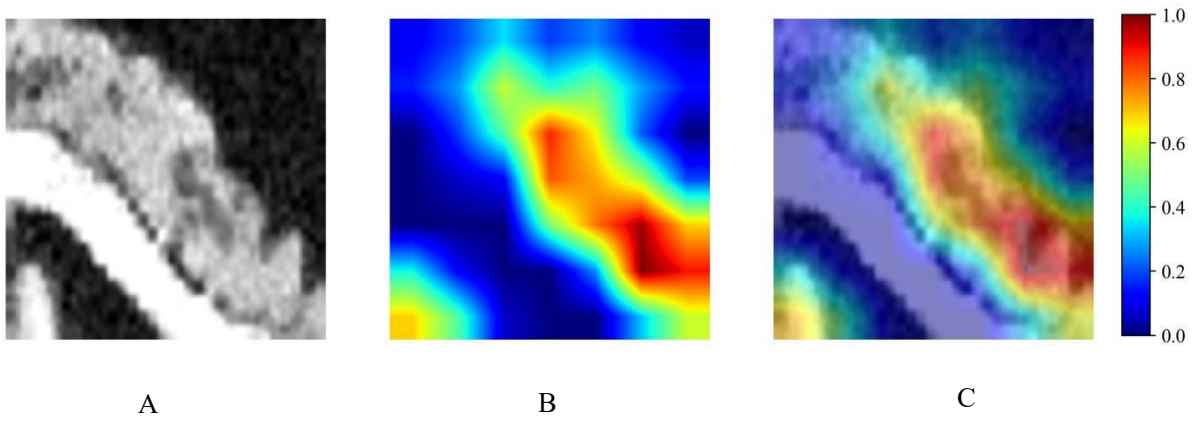
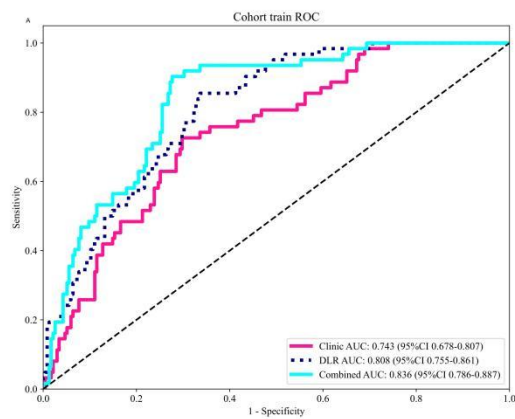
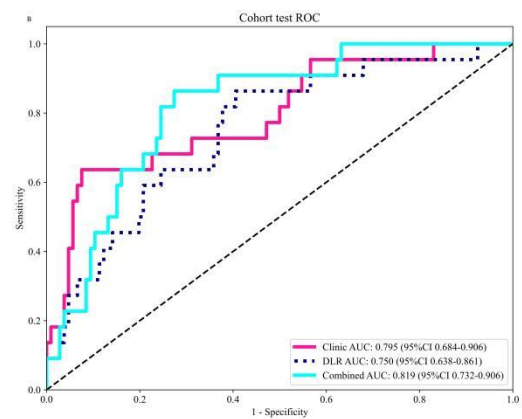


Figure 2 Deep learning attention maps overlaid on computed tomography images of patients from the test dataset.

(A) An axial computed tomography image of a patient with pancreatic cancer in the head of the pancreas (not shown). In the two attention maps (B and C), the activation gradient region is concentrated at the tail of the pancreatic body.



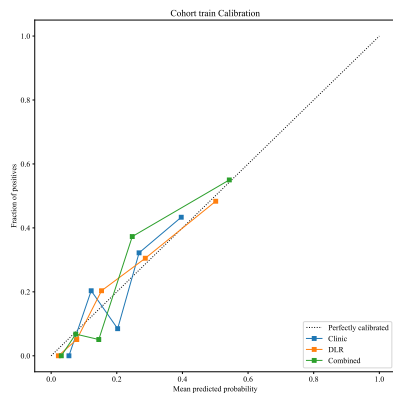
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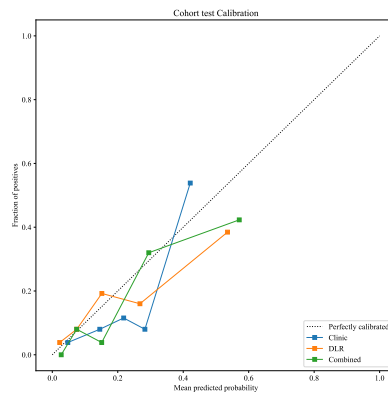
B

Figure 3 Comparison of receiver operating characteristic (ROC) curves of each model.

Comparison of ROC curves of each model in the training cohort (A). Comparison of ROC curves of each model in the test cohort (B).



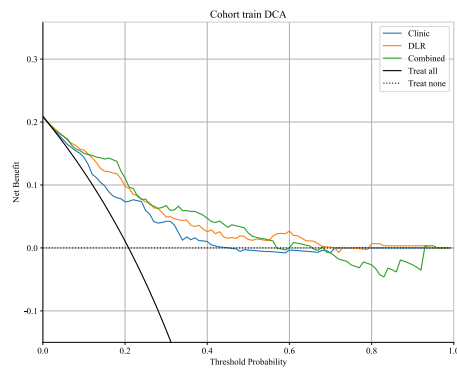
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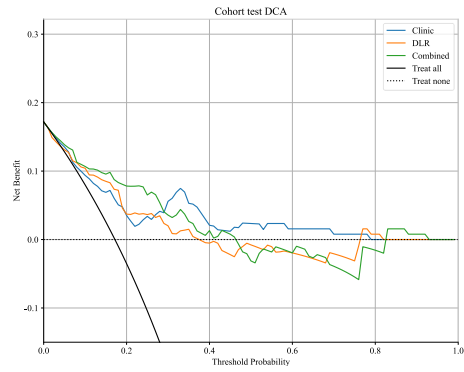
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Figure 4 Comparison of calibration curves of each model.

Calibration curves in the training cohort (A); Calibration curves in the test cohort (B)



A



B

Figure 5 Comparison of DCA curves of each model. DCA curves in the training cohort (A); DCA curves in the test cohort (B).

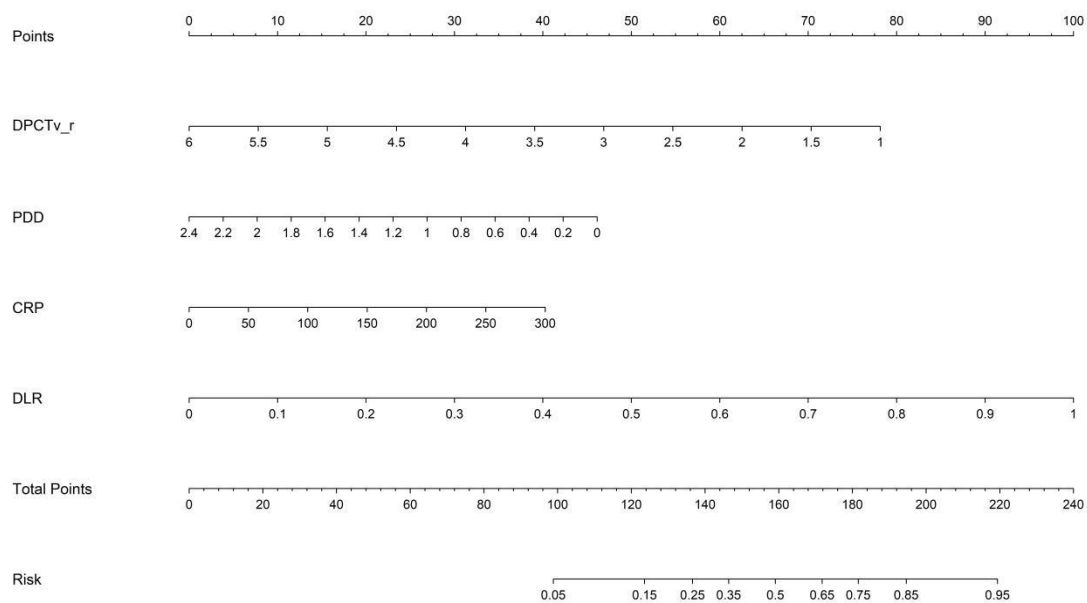


Figure 6 Nomogram for predicting the probability of CR-POPF in patients. CRP, C-reactive protein; PDD, Main pancreatic duct diameter; PDCTv-r, the ratio of pancreatic portal phase CT values to plain CT values outside the resection site; DLR, the Deep learning radiomics.

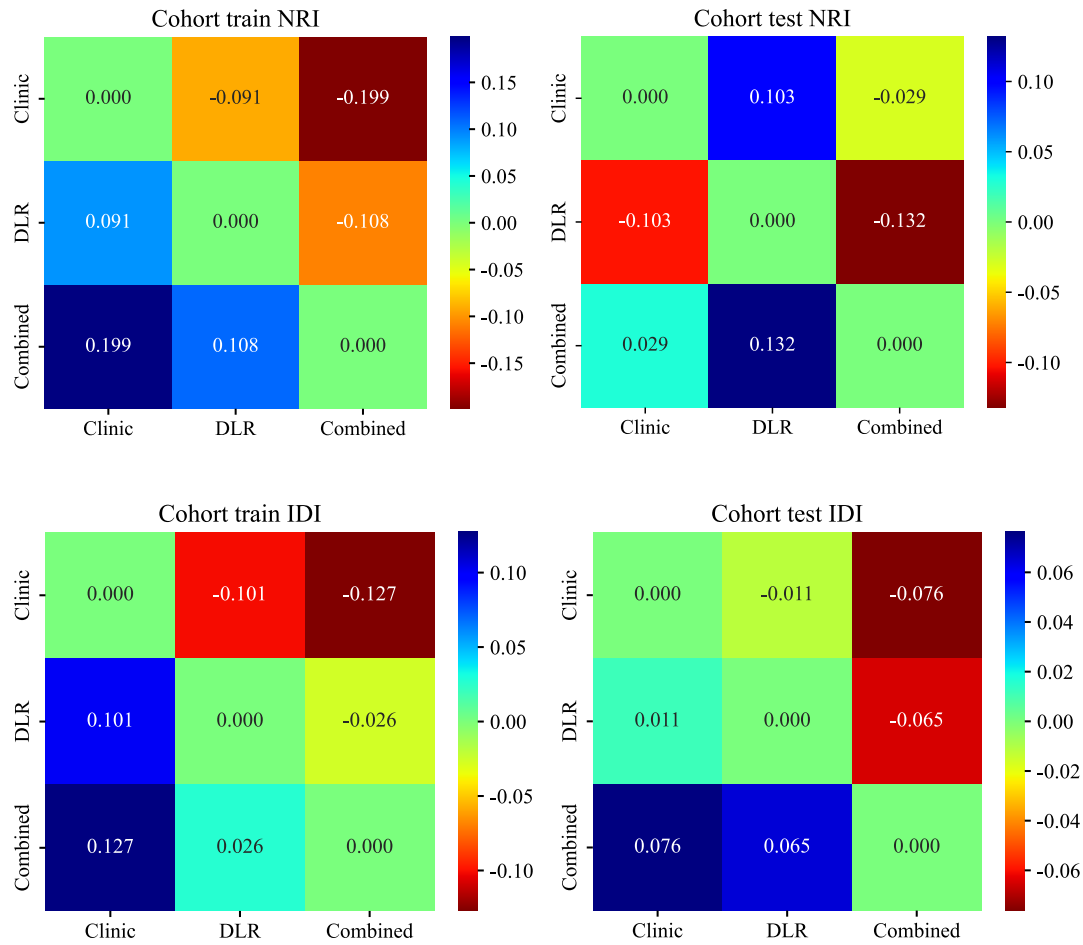


Figure 7 In cohort test and cohort train, Net Reclassification Improvement (NRI) and Integrated Discrimination Improvement (IDI) analyses demonstrated that the combined model significantly enhanced predictive accuracy and patient risk stratification relative to both the clinical and DLR-only models.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryA1.jpg](#)
- [SupplementaryA2.docx](#)