

Radiomics analysis based on plain X-rays to detect spinal fractures with posterior wall injury

Wangmi Liu^{1,*} , Xiaxuan Zhang^{2,*}, Ruofu Tang¹, Chengcheng Yu¹
and Guofang Sun³ 

Abstract

Purpose: Spinal fractures, particularly those involving posterior wall injury, pose a heightened risk of instability and significantly influence treatment strategies. This study aimed to improve early diagnosis and treatment planning for spinal fractures through radiomics analysis based on plain X-ray imaging.

Methods: This retrospective study analyzed plain X-rays of patients with spinal fractures at the thoracolumbar junction. Radiomic features were extracted from both anteroposterior and lateral plain spine radiographs to evaluate the utility of radiomics in detecting posterior wall injury. Diagnostic accuracy, sensitivity, and specificity of the radiomics models were assessed and compared with the performance of a spine surgeon.

Results: A total of 100 patients were included in the study, and four radiomic features were identified to construct radiomic signatures. In the training set, the RandomForest, ExtraTrees, and eXtreme Gradient Boosting (XGBoost) models achieved an area under the curve (AUC) of 1. In the validation set, the highest AUC value was 0.889, achieved by the RandomForest and XGBoost models. The diagnostic accuracy, sensitivity, and specificity of the radiomics models outperformed those of the spine surgeon.

Conclusions: Radiomics analysis based on plain X-ray imaging demonstrates significant potential for detecting posterior wall injury following spinal fractures. This approach offers a promising tool for early diagnosis and informed clinical decision-making in the management of spinal fractures.

Keywords

Radiomics, spinal fractures, posterior wall injury, X-ray, diagnose

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Introduction

Spinal fractures represent a serious skeletal injury, primarily resulting from extrinsic forces applied to the vertebral column. Common causes include motor vehicle accidents, falls from height, sports-related trauma, and other high-energy impacts.¹ Although these fractures are frequently observed in younger populations, they are increasingly becoming a significant health concern among the elderly due to their association with osteoporosis and age-related changes in spinal structure.² The consequences of spinal

¹The Second Affiliated Hospital, College of Medicine, Zhejiang University, Hangzhou, China

²Department of Clinical Medicine, The First Clinical College of Anhui Medical University, Hefei, China

³Shengzhou Hospital of Traditional Chinese Medicine, Shaoxing, China

*These authors have contributed equally to this work and share first authorship

Corresponding author:

Guofang Sun, Shengzhou Hospital of Traditional Chinese Medicine, Shaoxing, 312400, China.

Email: 14111210047@fudan.edu.cn



fractures can range from chronic pain, reduced mobility to potential neurological deficits. Treatment often requires extensive rehabilitation, and in some cases, surgical intervention to stabilize the affected region, particularly when instability increases the risk of further injury.³

Certain types of spinal fractures involve cortical defects in the posterior vertebral wall, which can exacerbate segmental instability.⁴ These fractures pose additional challenges for surgeons, as they carry a heightened risk of posterior cement leakage into the spinal canal during augmentation, potentially resulting in neurological complications.⁵ The advent of computed tomography (CT) scan with axial and sagittal reconstruction has greatly improved the visualization posterior wall injury. However, CT scans are more expensive than plain X-rays, expose patients to higher radiation levels and, in some regions, are restricted by insurance guidelines that prohibit simultaneous use of CT and MRI for fracture assessment.⁶ Plain X-rays, often the first imaging modality employed when a spinal fracture is suspected, are limited by the overlap of anatomical structures in two-dimensional images, making it difficult to detect subtle bone changes, such as posterior wall injury, with the naked eye.

Radiomics analysis, a field within computer science, aims to replicate human visual perception using advanced image processing techniques.⁷ Radiomics and machine learning offer promising potential for improving diagnostic accuracy and efficacy in musculoskeletal radiology, addressing a range of conditions including acute injuries,^{8,9} chronic disorders,^{10,11} spinal abnormalities, and neoplasms.¹² These algorithms, validated against ground truth data, can be effectively applied in clinical settings, such as detecting posterior wall injury associated with spinal fractures using plain X-rays.

In this study, radiomic features were extracted from fractured vertebrae using both anteroposterior (AP) and lateral views of plain X-rays. The objective was to evaluate the performance of a radiomics-based model for screening posterior wall injury in spinal fractures, utilizing standard pre-operative plain X-ray imaging.

Methods

Participants

This retrospective study was carried out at a single medical center. Spinal fractures commonly occur in transitional regions, such as the thoracolumbar junction (T10-L2). Between January 2019 and December 2023, all patients aged older than 18 years with fractures within this segment were reviewed. Exclusion criteria included patients with a history of malignancy, vertebral osteomyelitis, prior spinal surgery, multiple vertebral fractures, metabolic bone disease, or incomplete clinical data. Collected clinical information included gender, age, mechanisms of

injury, bone density, and the affected segment. Patients meeting the inclusion and exclusion criteria with complete clinical data were included in the analysis. The mechanisms of injury were categorized as either low-energy injuries from falls or high-energy injuries from trauma. The workflow of the proposed method is outlined in Figure 1. This research received approval from the Institutional Review Board of the Second Affiliated Hospital of Zhejiang University (2024-0266).

Gold standard for diagnosis

Human interpretation of CT scans was used as the reference standard for diagnosing posterior wall injury. Classification of patients with or without posterior wall injury was independently performed by two spine surgery residents based on CT images. In cases of disagreement, a joint review of the CT scans was conducted to reach a consensus.

For patients who did not undergo bone density testing, particularly younger individuals, Hounsfield unit (HU) values were calculated from Picture Archiving and Communication System data following a previously published methodology.¹³ Regions of interest (ROI) was placed on the midbody axial CT image for one vertebra above and one below the fractured vertebra. ROI was defined as elliptical regions encompassing the trabecular bone while avoiding cortical bone. Osteoporosis was diagnosed using a mean HU threshold of ≤ 110 HU.¹⁴

Plain X-ray technique

AP and lateral radiographs were obtained for all enrolled patients. The lowest mobile disc level was identified as L5/S1, regardless of lumbar anomalies. Radiographs were captured using a high-voltage generator (Philips Medical System) with an 81 kVp voltage, an average current of 20 mAs, and an exposure time of 25 ms. Images with improper positioning or unclear exposure were excluded from further analysis.

Radiomic features extraction

ROI of fractured vertebrae were delineated using ITK-SNAP software (version 4.0.2; <http://www.itksnap.org>). An example of delineation process is shown in Figure 2. Radiomic features were extracted using the “PyRadiomics” package (version 3.0.1) implemented in Python (version 3.9.7). Features were categorized into three categories: (I) geometry, (II) intensity, and (III) texture. Geometry features represent the three-dimensional shape characteristics of the tissue. Intensity features describe the first-order statistical distribution of voxel intensities within the tissue. Texture features capture patterns and higher-order spatial distributions of intensities.

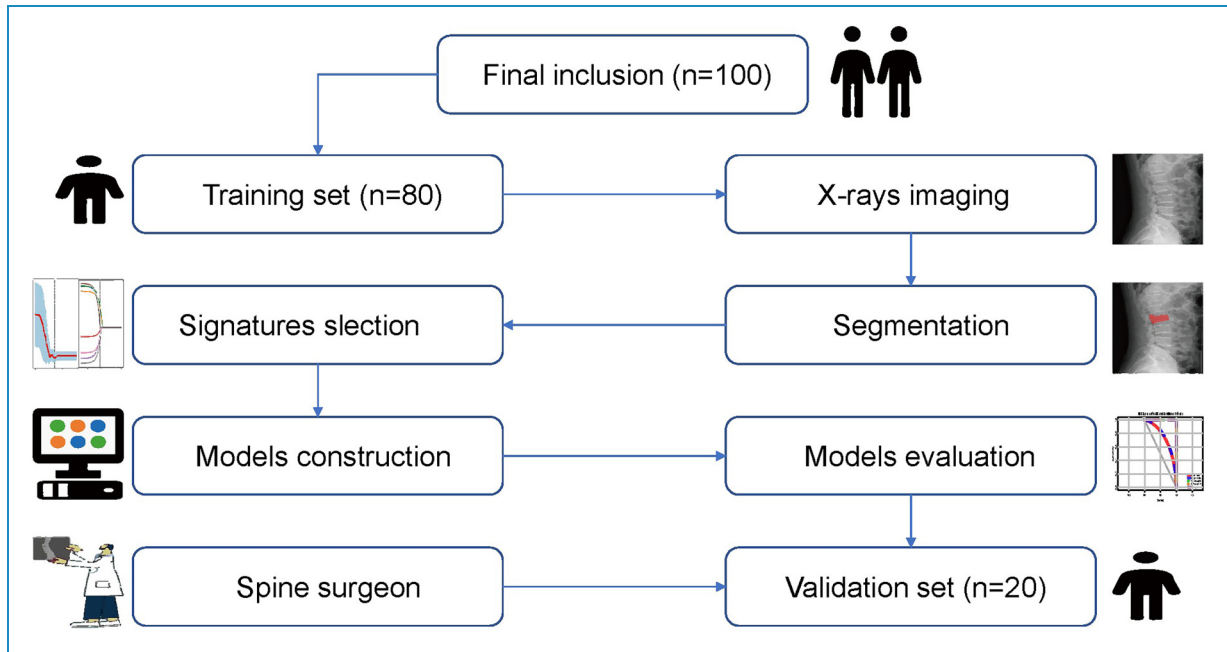


Figure 1. The overall workflow of the proposed method.

Radiomic features selection

After normalizing radiomic features with Z-score, we conducted a Student's t-test and retain features with p -values < 0.05 . Correlations between features were assessed using Spearman's rank correlation coefficient, and features with a correlation coefficient > 0.9 were reduced by randomly selecting one. The least absolute shrinkage and selection operator (LASSO) regression model was applied to the training dataset to identify significant features.¹⁵ The LASSO model shrinks regression coefficients and eliminates irrelevant features by adjusting the regularization weight (λ), which was optimized through 10-fold cross-validation.¹⁶ Features with nonzero coefficients were used to construct a radiomics signature, calculated as a linear combination of the retained features weighted by their coefficients. LASSO regression modeling was conducted using the scikit-learn package (version 0.24.2) in Python.

Evaluation of radiomics models

The final features from LASSO screening were used to build machine learning models, including logistic regression (LR), support vector machines (SVM), RandomForest, ExtraTrees, and eXtreme Gradient Boosting (XGBoost). Model performance was evaluated using the area under the curve (AUC) in both training and validation datasets. The accuracy, sensitivity, and specificity of the radiomics models were compared with those of a spine surgeon with five years of experience. Decision curve analysis was performed to assess the clinical utility of the models.

Statistical analysis

All statistical analyses were conducted using Python (version 3.9.7). Parametric variables were analyzed with a Student's t-test, while categorical variables were assessed using a χ^2 test. A p -value < 0.05 was considered statistically significant.

Results

Patient characteristics

The study included 100 patients (45 males, 55 females, median age 57.5 years, range 21–77 years) with thoracolumbar fracture who underwent an X-ray and CT at our hospital. Of these, 51 patients had an intact vertebral body posterior wall (Group 1), while 49 patients exhibited posterior wall injury (Group 2). To ensure imaging quality and a sufficient sample size, the study primarily focused on injured segments within the T12 to L2 range. Patient demographics are summarized in Table 1. Patients in Group 2 were significantly more likely to have sustained high-energy injury ($p = 0.038$) and lumbar fracture ($p = 0.045$). The original dataset was randomly divided into training (80%) and validation (20%) sets, with no statistically significant differences observed in demographic or clinical parameters between the two datasets.

Features extraction and selection

From the plain X-rays images, 1666 quantitative features were initially extracted. Based on a significance threshold

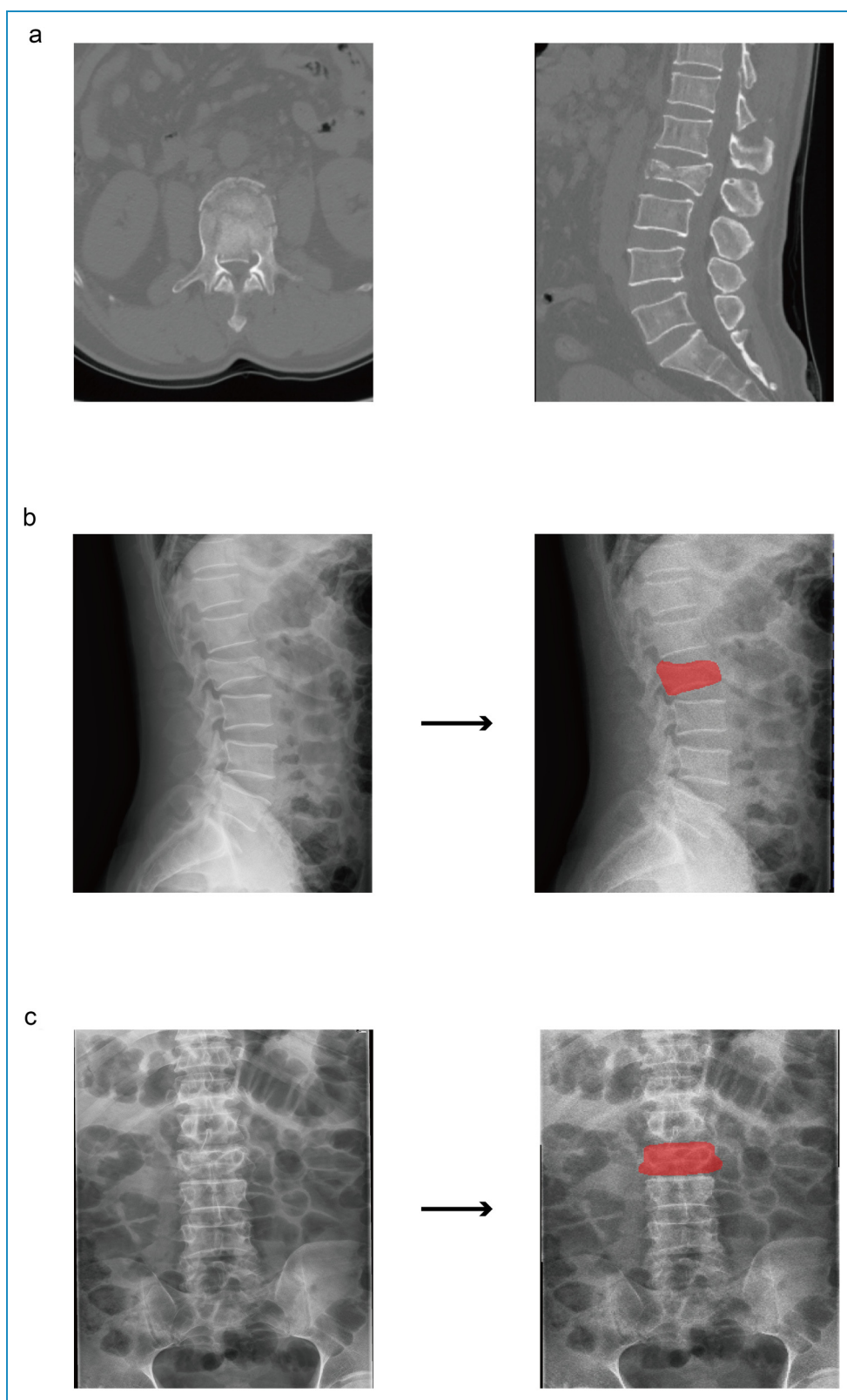


Figure 2. Delineation of the fractured vertebral body. (A) A 51-year-old man with an L2 fracture and posterior wall injury confirmed by CT scan. (B) Delineation on a lateral X-ray. (C) Delineation on an AP X-ray.

Table 1. Patient characteristics.

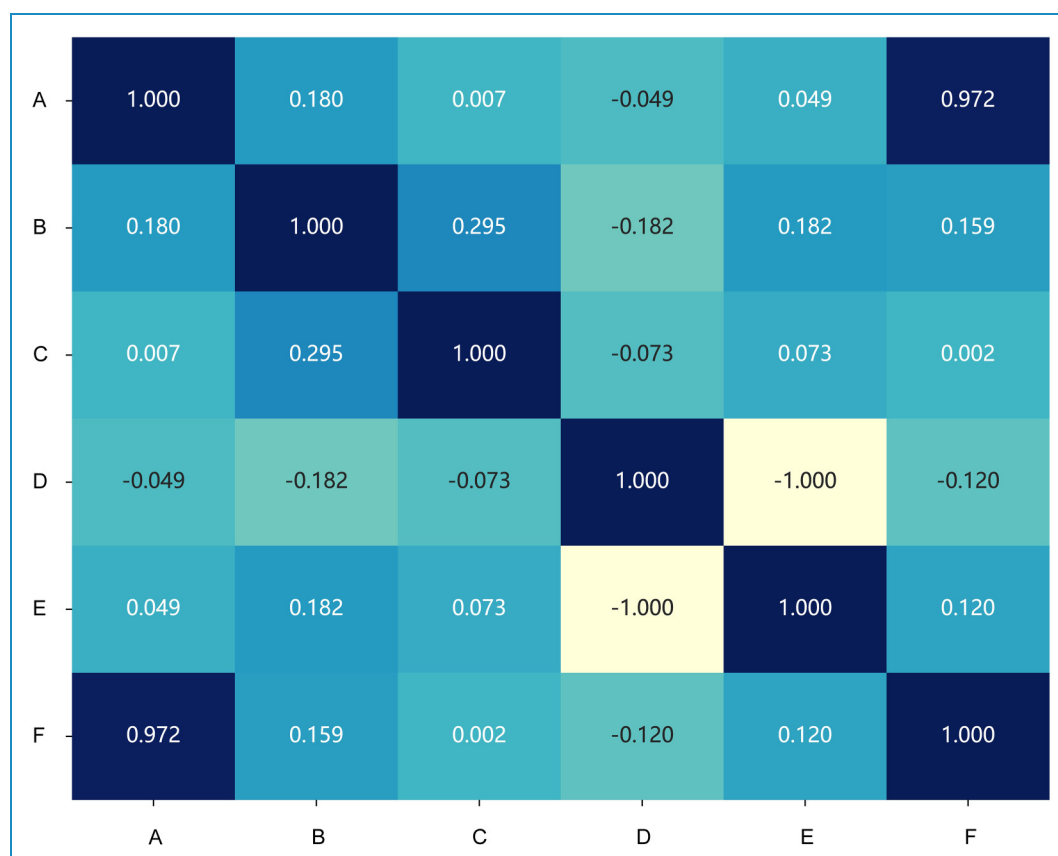
	All	Group 1 (n = 51)	Group 2 (n = 49)	p-value	Training set (n = 80)	Validation set (n = 20)	p-value
Age, mean (SD)	53.87 ± 12.56	55.47 ± 11.89	52.20 ± 13.14	0.195	54.21 ± 13.25	52.50 ± 9.45	0.588
Sex				0.410			0.132
Female, n (%)	55 (55.00)	26 (50.98)	29 (59.18)		47 (58.75)	8 (40.00)	
Male, n (%)	45 (45.00)	25 (49.02)	20 (40.82)		33 (41.25)	12 (60.00)	
Mechanisms of injury				0.038			0.388
Low energy, n (%)	41 (41.00)	26 (50.98)	15 (30.61)		35 (43.75)	6 (30.00)	
High energy, n (%)	59 (59.00)	25 (49.02)	34 (69.39)		45 (56.25)	14 (70.00)	
Injured segment				0.045			0.314
T12, n (%)	25 (25.00)	17 (33.33)	8 (16.33)		20 (25.00)	5 (25.00)	
L1, n (%)	53 (53.00)	21 (41.18)	32 (65.31)		40 (50.00)	13 (65.00)	
L2, n (%)	22 (22.00)	13 (25.49)	9 (18.37)		20 (25.00)	2 (10.00)	
Bone density				0.771			0.830
Normal, n (%)	68 (68.00)	34 (66.67)	34 (69.39)		54 (67.50)	14 (70.00)	
Osteoporosis, n (%)	32 (32.00)	17 (33.33)	15 (30.61)		26 (32.50)	6 (30.00)	

Boldface value represents a p-value less than 0.05.

Table 2. Features with p -value <0.05 .

Image type	Feature class	Feature name	Group 1	Group 2	p -value
Original	Shape	Elongation (AP)	0.25 ± 1.06	-0.25 ± 0.88	0.026
Wavelet HHH	Firstorder	Kurtosis (AP)	0.25 ± 1.33	-0.25 ± 0.35	0.027
Wavelet HHH	Glrlm	HighGrayLevelRunEmphasis (AP)	-0.24 ± 0.63	0.24 ± 1.23	0.032
Wavelet HHH	Glrlm	LowGrayLevelRunEmphasis (AP)	0.24 ± 0.63	-0.24 ± 1.23	0.032
Wavelet LLL	Firstorder	Maximum (AP)	-0.23 ± 0.95	0.23 ± 1.00	0.035
Original	Firstorder	Maximum (AP)	-0.23 ± 0.97	0.23 ± 0.99	0.039

AP: anteroposterior.

**Figure 3.** Spearman correlation coefficients of radiomic features. (A) original first-order Maximum (AP); (B) original shape Elongation (AP); (C) wavelet HHH firstorder Kurtosis (AP); (D) wavelet HHH glrlm HighGrayLevelRunEmphasis (AP); (E) wavelet HHH glrlm LowGrayLevelRunEmphasis (AP); (F) wavelet LLL firstorder Maximum (AP).

of $p < 0.05$, six features were selected for further analysis (Table 2). Correlation analysis revealed that the absolute correlation coefficients between the following pairs of features exceeded 0.9: original first-order Maximum (AP) and wavelet LLL first-order Maximum (AP), as well as wavelet

HHH GLRLM High Gray-Level Run Emphasis (AP) and wavelet HHH GLRLM Low Gray-Level Run Emphasis (AP) (Figure 3). To address multicollinearity, the computer randomly retained wavelet LLL first-order Maximum (AP) and wavelet HHH GLRLM Low Gray-Level Run Emphasis

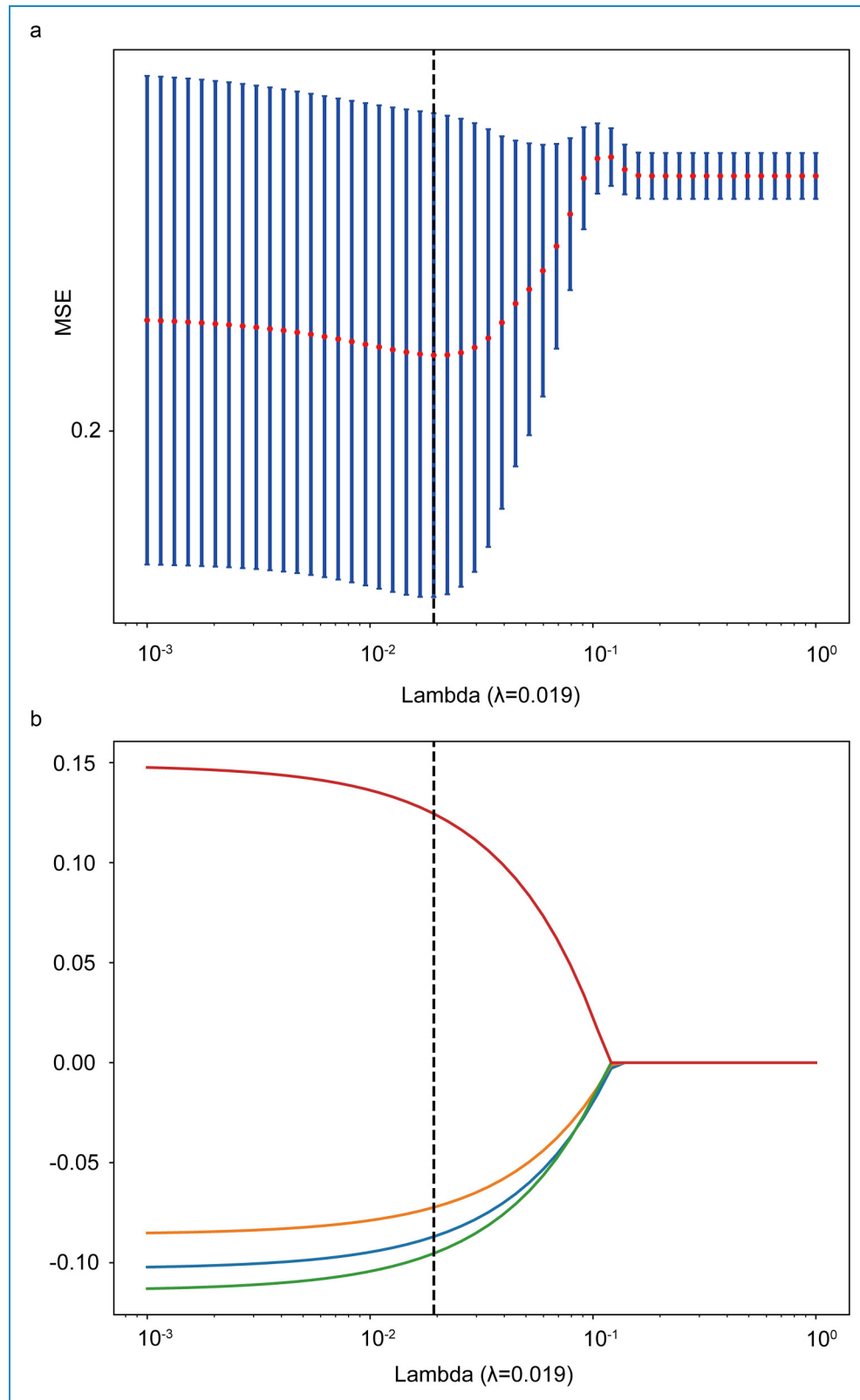


Figure 4. Selection of radiomic features using the LASSO regression model. (A) The vertical dotted line represents the tuning parameter (λ) on the x-axis. The y-axis shows the binomial deviance corresponding to each log (λ). (B) Coefficient profiles of four selected radiomic features versus log (λ).

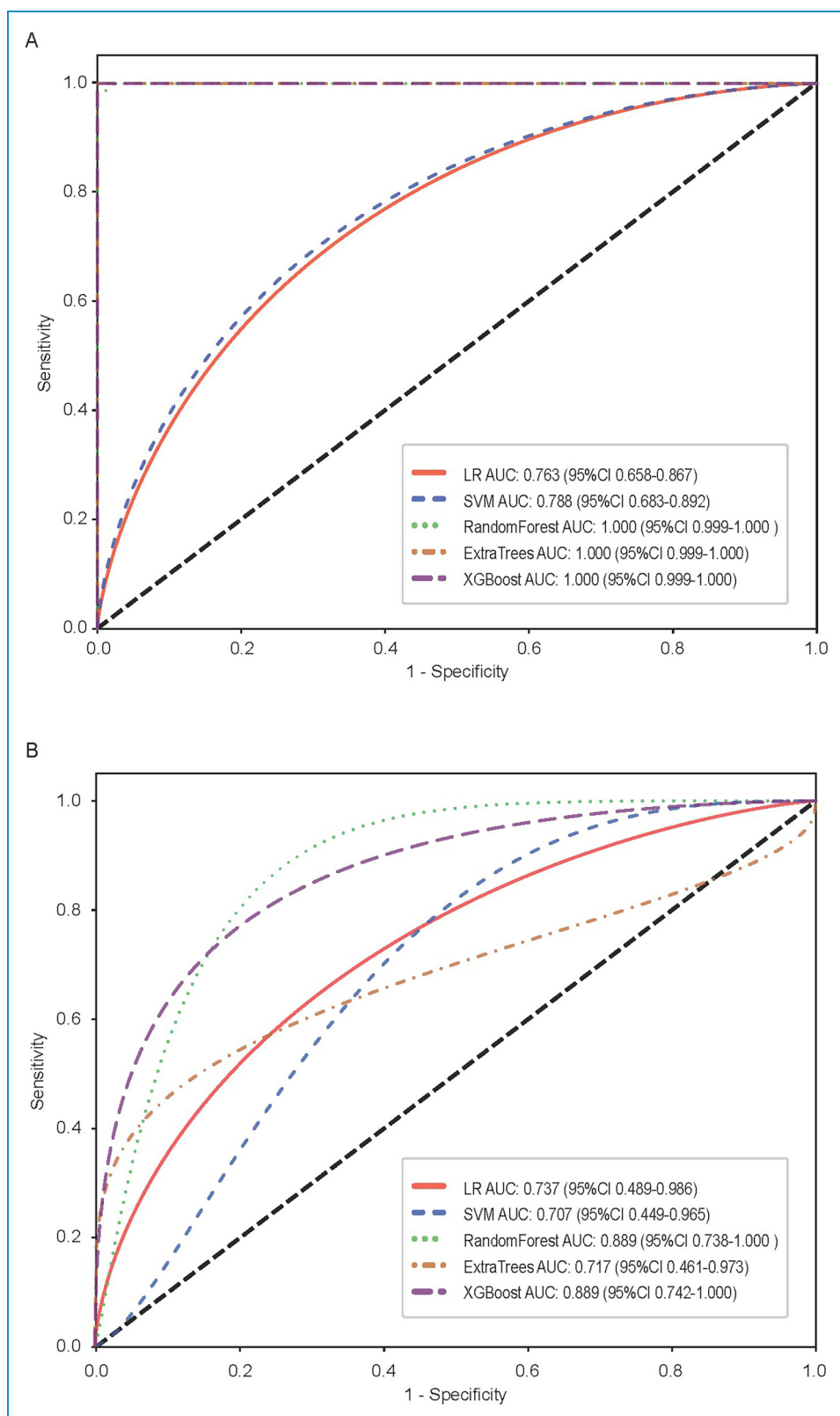


Figure 5. Receiver operating characteristic (ROC) analysis of the radiomic feature models. (A) Performance in the training dataset. (B) Performance in the validation dataset. (AUC: area under the curve).

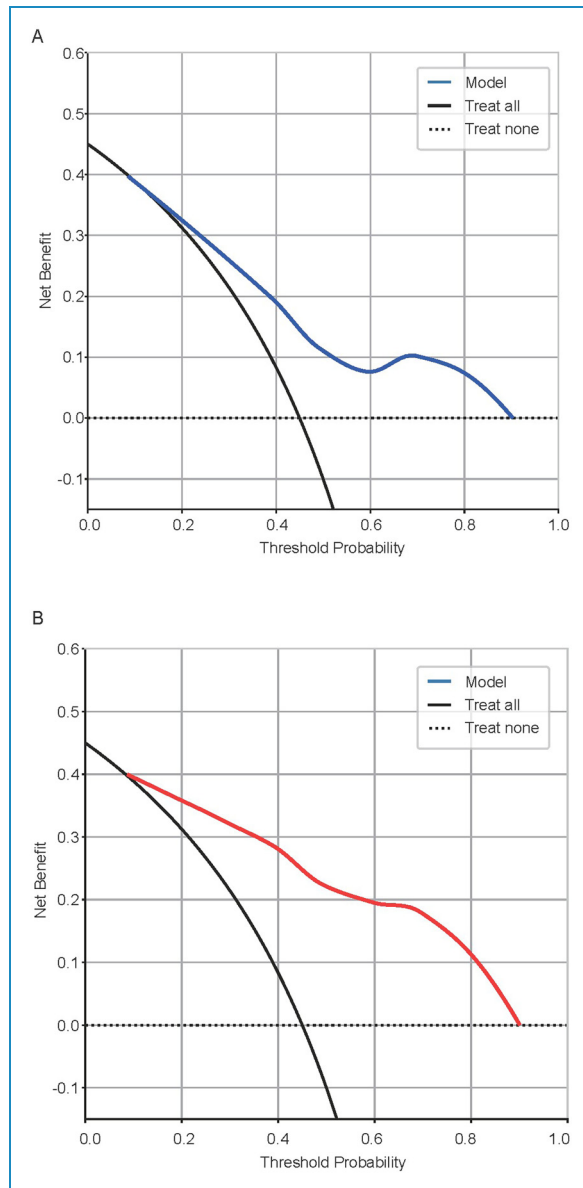


Figure 6. The decision curve analysis (DCA) analysis for the radiomic models. The x-axis represents the threshold probability, while the y-axis indicates the net benefit. The black line assumes all fractures have posterior wall injury, and the dotted line assumes no posterior wall injury in any fractures. (A) The RandomForest model. (B) The XGBoost model.

(AP) for analysis. Using an optimal λ value of 0.019, four features were ultimately selected to construct the radiomics signature (Figure 4).

Performance of radiomics feature models

The performance of the radiomics models, as evaluated by receiver operating characteristic curves, is shown in Figure 5. In the training dataset, the RandomForest, ExtraTrees, and XGBoost models achieved the maximum

Table 3. The comparison between human predictions and model predictions.

Prediction	Accuracy (%)	Sensitivity	Specificity
LR	65	0.67	0.64
SVM	70	0.67	0.73
RandomForest	75	0.89	0.64
XGBoost	75	0.67	0.82
ExtraTrees	55	0.22	0.82
Spine surgeon	60	0.67	0.55

AUC value of 1. In the validation dataset, the highest AUC value, 0.889, was obtained with the RandomForest and XGBoost models. The clinical benefits of these models in the validation datasets are demonstrated in Figure 6. In terms of diagnostic, the spine surgeon outperformed the ExtraTrees model but was inferior to all other models (Table 3).

Discussion

This study aimed to evaluate the diagnostic precision of plain X-rays enhanced by machine learning for detecting posterior wall injury, comparing its performance to that of a spine surgeon. Our findings demonstrate that plain radiographs, when analyzed using radiomic approaches, achieve acceptable diagnostic accuracy, often surpassing the expertise spine surgeon.

Spinal fractures present significant challenges in spinal surgery, requiring a nuanced understanding of associated injuries for comprehensive management. Among the various types of vertebral fractures, those involving the posterior wall of the vertebral body warrant particular attention due to their implications for spinal stability and neurological integrity. Early report indicates that up to 47.4% of patients with posterior wall injury experience bone cement leakage during kyphoplasty.¹⁷ Although most leakages are asymptomatic,¹⁸ catastrophic complication, such as intradural cement leakage,¹⁹ inferior vena cava syndrome,²⁰ and pulmonary embolism,²¹ have been reported. For patients receiving conservative treatment for osteoporotic spinal fractures, posterior wall injury is a risk factor for long-term pain.²² Conversely, young patients with spinal fractures are often managed with internal fixation. Finite-element analysis has shown that posterior wall injury increase the risk of failure in short-segment internal fixation strategies.²³ Therefore, accurate diagnosis is critical for formulating an appropriate treatment plan. CT remains the gold standard for delineating posterior wall injury.²⁴

However, our findings suggest that when CT is unavailable, radiomic analysis of plain X-rays can provide reliable diagnostic results. In fact, this approach was comparable to the performance of specialized spine surgeons, except for the ExtraTrees model, which demonstrated acceptable performance on the training set but underperformed on the validation set, likely due to overfitting.

Interestingly, although features were extracted from both AP and lateral X-rays, the final radiomic signature was based entirely on features derived from AP views. In contrast, the spine surgeon relied predominantly on lateral X-rays to assess posterior wall injuries. This reliance can be attributed to two key factors: firstly, AP X-rays often suffer from overlapping structures and interference from intestinal gas, which obscure details; secondly, lateral X-rays provide direct visualization of vertebral compression. Previous studies have demonstrated a correlation between the degree of spinal canal encroachment and the changes in posterior vertebral body height.²⁵ Radiomics, as an emerging field in medical imaging, utilizes advanced computational techniques to extract intricate details that elude human observation. By leveraging sophisticated algorithms, radiomics unveils subtle textures, patterns, and relationships within medical images, offering insights beyond conventional visual observation.²⁶ The present study demonstrated that radiomics models based on four selected features could effectively screen for posterior wall injury, highlighting its potential utility in clinical practice.

This study has several limitations. First, it was a retrospective, single-center study. Future prospective studies with larger, multi-center cohorts are needed to validate the findings. Second, the study focused on patients with relatively mild spinal fractures, excluding cases with fracture dislocations. Therefore, the conclusions should be extrapolated with caution to more severe spinal injuries. Third, the high quality of the imaging in this study may not reflect real-world scenarios, where variations in patient positioning and bowel gas artifacts could affect model performance.

Conclusion

In conclusion, we developed and validated a radiomic signature model based on plain X-rays for identifying posterior wall injury after spinal fractures. This radiomic approach holds significant potential for providing valuable diagnostic insights, guiding therapeutic decision-making, reducing additional medical costs, and minimizing radiation exposure.

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Availability of data and materials: Data are available on request from the authors.

Contributorship: GS developed the study concept and design. WL and XZ analyzed the data, and drafted the manuscript. RT and CY were responsible for data collection and validation. RT carried out the statistical analyses. GS interpreted the results. All the authors participated in all stages of the preparation of the manuscript and approved the final version submitted for publication.

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ORCID iDs: Wangmi Liu  <https://orcid.org/0000-0002-9012-0801>

Guofang Sun  <https://orcid.org/0009-0005-2157-3494>

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