

# Diagnosis of traumatic liver injury on computed tomography using machine learning algorithms and radiomics features: The role of artificial intelligence for rapid diagnosis in emergency rooms

Hanieh Alimiri Dehbaghi<sup>1</sup>, Karim Khoshgard<sup>2</sup>, Hamid Sharini<sup>3</sup>, Samira Jafari Khairabadi<sup>4</sup>

<sup>1</sup>Department of Medical Physics, Student Research Committee, University of Medical Sciences, Kermanshah, Iran, <sup>2</sup>Department of Medical Physics, University of Medical Sciences, Kermanshah, Iran, <sup>3</sup>Department of Biomedical Engineering, University of Medical Sciences, Kermanshah, Iran, <sup>4</sup>Department of Biostatistics, Student Research Committee, University of Medical Sciences, Kermanshah, Iran

**Background:** The initial assessment of trauma is a time-consuming and challenging task. The purpose of this research is to examine the diagnostic effectiveness and usefulness of machine learning models paired with radiomics features to identify blunt traumatic liver injury in abdominal computed tomography (CT) images. **Materials and Methods:** In this study, 600 CT scan images of people with mild and severe liver damage due to trauma and healthy people were collected from the Kaggle dataset. The axial images were segmented by an experienced radiologist, and radiomics features were extracted from each region of interest. Initially, 30 machine learning models were implemented, and finally, three machine learning models were selected including Light Gradient-Boosting Machine (LGBM), Ridge Classifier, and Extreme Gradient Boosting (XGBoost), and their performance was examined in more detail. **Results:** The two criteria of precision and specificity of LGBM and XGBoost models in diagnosing mild liver injury were calculated to be 100%. Only 6.00% of cases were misdiagnosed by the LGBM model. The LGBM model achieved 100% sensitivity and 99.00% accuracy in diagnosing severe liver injury. The area under the receiver operating characteristic curve value and precision of this model were also calculated to be 99.00% and 98.00%, respectively. **Conclusion:** The artificial intelligence models used in this study have great potential to improve patient care by assisting radiologists and other physicians in diagnosing and staging trauma-related liver injuries. These models can help prioritize positive studies, allow more rapid evaluation, and identify more severe injuries that may require immediate intervention.

**Key words:** Artificial intelligence, liver, machine learning, radiomics

**How to cite this article:** Alimiri Dehbaghi H, Khoshgard K, Sharini H, Khairabadi SJ. Diagnosis of traumatic liver injury on computed tomography using machine learning algorithms and radiomics features: The role of artificial intelligence for rapid diagnosis in emergency rooms. *J Res Med Sci* 2024;29:77.

## INTRODUCTION

Trauma is the leading cause of death in the first four decades of life and the third most common reason for mortality, regardless of age.<sup>[1]</sup> The number of deaths caused by trauma worldwide is estimated to be over 5 million annually.<sup>[2]</sup> Intra-abdominal injuries (any damage to intraperitoneal and retroperitoneal organs) following blunt trauma (80%) or penetrating

trauma (20%) cause a significant part of trauma-related deaths.<sup>[3]</sup> In emergency departments, most of the cases involving abdominal trauma (80%) are classified as "blunt abdominal trauma" (BAT) and the mortality rate for this type of trauma is much higher than that for penetrating trauma.<sup>[4]</sup> This kind of trauma is a significant diagnostic challenge in most cases. Patients with severe injuries and continuous bleeding need immediate identification and treatment.<sup>[5]</sup> Abdominal trauma is often not diagnosed through physical examination,

This is an open access journal, and articles are distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 License, which allows others to remix, tweak, and build upon the work non-commercially, as long as appropriate credit is given and the new creations are licensed under the identical terms.

**For reprints contact:** WKHLRPMedknow\_reprints@wolterskluwer.com

### Access this article online

Quick Response Code:



Website:

<https://journals.lww.com/jrms>

DOI:

10.4103/jrms.jrms\_847\_23

**Address for correspondence:** Dr. Karim Khoshgard, Department of Medical Physics, University of Medical Sciences, Kermanshah, Iran.  
E-mail: khoshgardk@gmail.com

**Submitted:** 27-Dec-2023; **Revised:** 11-Jun-2024; **Accepted:** 02-Jul-2024; **Published:** 31-Dec-2024

patient symptoms, or laboratory tests. Therefore, rapid diagnosis of abdominal trauma using medical imaging is very important for patient care.<sup>[6,7]</sup>

The liver is the most common abdominal organ involved in blunt abdominal trauma due to its anterior location, large size, and fragile parenchyma. Early diagnosis and assessment of the severity of liver trauma are both important for triage and optimal treatment of trauma patients.<sup>[8-10]</sup> Contrast-enhanced computed tomography (CT) is considered the gold standard technique for evaluating liver trauma and monitoring its progression over time.<sup>[9,11]</sup>

Trauma evaluation can be a difficult task for even the most experienced radiologist. When there are multiple injuries, doctors may focus only on the most obvious or significant injury and ignore the possibility of other injuries.<sup>[12]</sup>

Machine learning is a subset of artificial intelligence that provides an effective way to automate the analysis and recognition of medical images. It has the potential to reduce the workload of radiologists in radiology practice. Machine learning is the study of computer algorithms that can learn complex relationships and patterns from empirical data and make accurate decisions.<sup>[13]</sup>

Radiomics generally aims to extract quantitative and ideally reproducible information from diagnostic images, including complex patterns that are difficult to detect or quantify with the human eye.<sup>[14,15]</sup>

Artificial intelligence and radiomics approaches applied to medical image processing for noninvasive disease characterization have increased dramatically in recent years.<sup>[16]</sup>

In a 2021 study by Brejneboel *et al.*, with the aim of investigating the diagnostic performance of an artificial intelligence algorithm for the diagnosis of pneumoperitoneum in CT scan images in patients with acute abdominal pain, the area under the receiver operating characteristic curve (AUC) was calculated to be 77%, and the specificity was 99%.<sup>[17]</sup>

Both early detection and severity assessment of liver trauma are critical for optimal triage and treatment of trauma patients.<sup>[18]</sup> The purpose of this study is to evaluate the performance of several machine learning models in diagnosing mild and severe liver complications caused by trauma in CT scan images using radiomics features, to improve the speed and accuracy of doctors' performance and subsequently the quality of providing health services.

## MATERIALS AND METHODS

This study was performed in line with the principles of

the Declaration of Helsinki. Approval was granted by the Ethics Committee of Kermanshah University of Medical Sciences (IR.KUMS.MED.REC.1402.281).

### Data

For this study, 600 axial CT slices from the Kaggle dataset<sup>[19]</sup> were utilized, of which 200 slices related to healthy liver, 200 slices with mild liver damage, and the remaining 200 slices with serious liver damage caused by blunt trauma. The images were DICOM, and the matrix size was 512 × 512. The thickness of the slices ranged from 0.5 to 5 mm.

### Segmentation

The process of dividing the image into constituent parts to extract the desired areas is called segmentation. CT scan images were segmented in three-dimensional (3D) Slicer software (version 5.4.0) with the cooperation of an experienced radiologist. The injured area in the liver was segmented and separated from the image. In the case of healthy images, the entire parenchyma of the liver was segmented.

### Extraction of features = Radiomics

This step refers to the concept of radiomics and was done with the radiomics toolbox in 3D Slicer software. The extracted features include two sets of features: first-order statistical features and texture features including gray-level co-occurrence matrix, gray-level dependence matrix, gray-level run-length matrix, gray-level size zone matrix, and neighboring gray-tone difference matrix. These features are obtained using Wavelet filters with different decompositions (all possible combinations using a high-pass or low-pass filter in all three dimensions including HHH, HHL, HLH, HLL, LHH, LHL, LLH, and LLL). All these features were saved in an Excel file.

Wavelet analysis of an image is possible using a pair of square mirror filters, a high-pass filter, and a low-pass filter.<sup>[20]</sup> The high-pass filter highlights the changes in the gray level and therefore emphasizes the details of the image, whereas the low-pass filter smoothes the image in terms of the gray level and removes the details of the image.<sup>[21]</sup>

The machine learning models used in this research do not need a feature selection algorithm separately and these models automatically select a number of features and based on the importance of that feature in decision-making by the model the scores are assigned to it. The most important features that are involved in decision-making by models in CT scan images are given in Table 1. Considering that these characteristics have shown their importance in the diagnosis of liver lesions after trauma, they can be considered suitable candidates for biological markers in liver damage, so it is suggested that in future studies, the correlation between these characteristics should be examined with clinical parameters.

**Table 1: The most important features selected by the models**

<b>LGBM</b>	<b>XGBoost</b>	<b>Ridge classifier</b>
First order	First order	First order
Median (HLH)	10 Percentile (LLH)	Energy (HLL)
Mean (HLH)	Robust Mean Absolute Deviation (LLH)	Total Energy (HLL)
90 Percentile (o)	10 Percentile (LHL)	
Kurtosis (o)	90 Percentile (LHL)	
Mean (HLL)	Root Mean Squared (HLL)	
Median (LHL)	Root Mean Squared (LLL)	
Mean Absolute Deviation (o)	Variance (LLL)	
10 Percentile (LLH)	90 Percentile (o)	
	10 Percentile (o)	
	Kurtosis (o)	
	10 Percentile (LLH)	
GLCM	GLCM	
Cluster Tendency (o)	IMC2 (o)	
IMC1 (o)	Joint Energy (LHH)	
IMC2 (HLL)-	IMC1 (HHL)	
IMC2 (o)	Difference Variance (LLL)	
Sum Entropy (o)	Sum Entropy (LLL)	
	Cluster Tendency (o)	
	Sum Entropy (o)	
	Autocorrelation (LLL)	
	Inverse Variance (LLL)	
GLDM	GLDM	
Small Dependence Emphasis (LHL)	Small Dependence Emphasis (HLL)	
Dependence Entropy (o)	Dependence Entropy (o)	
Dependence Variance (o)	Dependence Variance (HLH)	
Dependence Entropy (LLL)		
Large Dependence High Gray Level Emphasis (LLL)		
Large Dependence Low Gray Level Emphasis (LLL)		
Dependence Nonuniformity Normalized (o)		
GLRLM	GLRLM	
Run Entropy (LLH)	Run Entropy (o)	
Run Entropy (o)	Gray Level Nonuniformity Normalized (o)	
Gray Level Nonuniformity Normalized (o)	Gray Level Nonuniformity Normalized (LLH)	
	Short-Run Emphasis (LHH)	
	Short-Run Emphasis (LLL)	
	GLSZM	GLSZM
	Zone Entropy (LHL)	Large Area Emphasis (o)
	Size Zone Nonuniformity (HLL)	Zone Variance (o)
	Small Area Low Gray Level Emphasis (HLL)	Zone Variance (LHL)
		Large Area Low Gray Level Emphasis (HLH)
		Large Area Emphasis (LLL)
		Zone Variance (LLL)
		Large Area Emphasis (LLH)
		Large Area Emphasis (LHH)
		Large Area Low Gray Level Emphasis (LHH)
		Zone Variance (LLH)
	NGTDM	
	Strength (O)	

LGBM=Light Gradient-Boosting Machine; XGBoost=Extreme Gradient Boosting; GLCM=Gray-level co-occurrence matrix; GLSZM=Gray-level size zone matrix; NGTDM=Neighboring gray-tone difference matrix; GLRLM=Gray-level run-length matrix; GLDM=Gray-level dependence matrix; H= high pass; L= low pass; All possible combinations using a high pass or low pass filter in all three dimensions including HHH, HHL, HLH, HLL, LHH, LHL, LLH, and LLL; IMC1=Informational Measure of Correlation; O= original (without applying the wavelet filter)

### Training of machine learning models

To train learning models, first, the data were divided into two parts: training data and test data. In this study, 75% of the data (slices) were used for training, and 25% of the data were also assigned to test the algorithms. These kinds of issues are supervised learning issues; they need labels. In supervised learning, each sample contains two

parts: one is input observations or features and the other is output observations or labels.<sup>[22,23]</sup> In this study, the input observations are radiomics features and the output observations are the presence or absence of kidney injuries. The purpose of supervised learning is to conclude a functional relationship from training data that generalizes well to testing data.<sup>[13]</sup> As typical of supervised machine

learning scenarios, the output variable, expertly coded by medical professionals, is incorporated into the Excel file housing the radiomics features, facilitating its provision to the machine learning model.

Radiomics features get saved into an Excel file. Then, during machine learning model training, Python calls the Excel sheets and processes them into the standard tables used to train classifiers:

- `df = pd.read_excel("CT.xlsx")`

Then, the variables  $x$  (independent variables = radiomics features) and  $y$  (dependent variable = output or target) are defined as follows:

- `x = df.iloc[:,1:633]`
- `y = df.iloc[:,633]`

Here is a brief description of each of the models:

Light Gradient-Boosting Machine (LGBM) is a high-speed, distributed, high-performance machine learning framework based on a decision tree algorithm. This framework can be used in various tasks such as sorting, classification, regression, and other machine learning tasks. By maintaining accuracy, the speed of this framework increases about ten times, and the amount of occupied memory is about three times less. This framework has advantages such as high training efficiency, low memory occupancy, high precision, and support for parallelization, and it can also be implemented using graphics processing units to process large data.<sup>[24]</sup>

Extreme Gradient Boosting (XGBoost) is an extension based on Gradient Boosting Machines. Its superior performance has been demonstrated in many data science competitions, and its multicore algorithms allow multiple tasks to be executed simultaneously, enabling the algorithm to scale to large datasets.<sup>[24,25]</sup>

The Ridge Classifier is a linear classification algorithm that is based on the Ridge Regression Algorithm. It is used to classify data into two or more classes based on features. In Ridge Regression, the objective is to minimize the sum of squared errors between the predicted values and the actual values.<sup>[26]</sup>

### Performance evaluation of models

In research related to disease diagnosis with different machine learning algorithms, the results are usually evaluated with different criteria of confusion matrix. In this study, accuracy, precision, sensitivity, specificity, F1-score, misclassification area under the receiver operating characteristic curve (AUC) are measured. Table 2 shows how to calculate these criteria.<sup>[21,24]</sup>

**Table 2: Evaluation metrics for machine learning models and their formulas**

Metric	FORMULA
Precision	$\frac{TP}{TP + FP}$
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
Sensitivity	$\frac{TP}{TP + FN}$
Specificity	$\frac{TN}{TN + FP}$
F1-score	$\frac{2TP}{2TP + FP + FN}$
Misclassification	1 - accuracy

TN=True negative; FN=False negative; FP=False positive; TP=True positive

In our study:

- True positive: Instances where the model correctly predicts the hepatic injury in samples that have this injury
- True negative: Instances where the model correctly predicts the absence of hepatic injury in samples that do not have this injury
- False positive: Instances where the model incorrectly predicts the presence of hepatic injury in samples that do not have this injury
- False negative: Instances where the model incorrectly predicts the absence of hepatic injury in samples that have this injury.

## RESULTS

You can see the confusion matrix related to the implementation of models in CT scan images in Table 3.

According to Table 4, in terms of accuracy, the LGBM model has the best performance with a value equal to 99.00% in diagnosing severe liver damage and 94.00% for mild liver damage. In terms of precision criteria, LGBM and XGBoost models with a value equal to 100% showed a stronger performance than the Ridge Classifier model in detecting mild liver damage. For severe injuries, the precision of these two models was calculated as 98.00% and 96.00%, respectively. The AUC value for the LGBM model in diagnosing mild liver injuries was 93.80% and for severe injuries was 99.00%, which indicates a stronger performance of this model than the other two models.

Regarding the sensitivity criterion, the LGBM model has surpassed the other two models with values of 88.00% and 100%, respectively, in detecting mild and severe injuries. LGBM and XGBoost models achieved 100% specificity in detecting mild liver injuries, and for severe injuries, the

sensitivity of these two models was 98.00% and 96.00%, respectively. The F1-score, which is a combination of precision and recall criteria, was calculated as 93.00% and 99.00% for the LGBM model in diagnosing mild and severe liver damage, respectively.

Misclassification indicates the number of samples that have been incorrectly classified, and in this sense, the LGBM model has a better performance than the other two models with values equal to 6.00% and 1.00%, respectively, in detecting mild and severe liver damage.

## DISCUSSION

The use of contrast-enhanced CT is currently the gold standard for the diagnosis of liver injury following trauma.<sup>[8]</sup> According to the CT scan results, along with the patient's physiological condition, the medical team will determine the type of treatment and prognosis related to the complication. Early diagnosis of

injuries is critical to provide appropriate monitoring and treatment to the patient. Early detection of injuries prevents the occurrence of late complications and reduces the rate of death due to trauma.<sup>[9]</sup> However, initial trauma assessment is a very time-sensitive and challenging process. A multidisciplinary team performs multiple assessments and procedures simultaneously during the initial trauma assessment, and many critical decisions are made during this time. In addition to the cognitive bias of team members, conditions such as patients' instability, incomplete relevant clinical information, mental and physical fatigue, and excessive workload of physicians impair the performance of diagnosis and create an environment that is prone to medical errors. In fact, more diagnostic errors occur in the emergency department than anywhere else.<sup>[27,28]</sup> Timely diagnosis of injuries and prompt initiation of appropriate care are required to prevent further damage in future. The main challenge of emergency departments when treating trauma patients is the timely diagnosis of life-threatening injuries and initiation of appropriate treatment without delay.<sup>[29]</sup>

Artificial intelligence has attracted a lot of attention in recent years due to its excellent performance in image recognition tasks.

In this study, we proposed three machine learning models with the aim of timely diagnosis of liver injuries caused by trauma. Using these models can help doctors in the correct management of trauma patients and their timely treatment.

In a study conducted in 2022 with the aim of automatic diagnosis and quantitative assessment of liver trauma by Farzaneh *et al.*, deep convolutional neural network was used to segment the liver. The Dice/recall/precision coefficients of the proposed segmentation models were 96.13/96.00/96.35% and 51.21/53.20/56.76%, respectively, in segmenting liver parenchyma and liver trauma regions.<sup>[18]</sup> In this study, deep learning algorithms were used for automatic liver segmentation.

The most important limitation of this study is the lack of access to patients' clinical information. The use of other patient information such as clinical symptoms and the results of various clinical tests in the training of machine learning models can help to improve the performance accuracy of the models.

**Table 3: Confusion matrix for mild and severe liver injury**

Model	Mild liver injury	
	Predicted negative	Predicted positive
LGBM		
Actual negative	51 (TN)	0 (FP)
Actual positive	6 (FN)	43 (TP)
XGBoost		
Actual negative	51 (TN)	0 (FP)
Actual positive	7 (FN)	42 (TP)
Ridge classifier		
Actual negative	51 (TN)	0 (FP)
Actual positive	6 (FN)	43 (TP)
Model	Severe liver injury	
	Predicted negative	Predicted positive
LGBM		
Actual negative	50 (TN)	1 (FP)
Actual positive	0 (FN)	49 (TP)
XGBoost		
Actual negative	49 (TN)	2 (FP)
Actual positive	1 (FN)	48 (TP)
Ridge classifier		
Actual negative	45 (TN)	6 (FP)
Actual positive	5 (FN)	44 (TP)

LGBM=Light Gradient-Boosting Machine; XGBoost=Extreme Gradient Boosting; TN=True negative; FN=False negative; FP=False positive; TP=True positive

**Table 4: The results of implementing the models**

Injury	Models	Accuracy (%)	Precision (%)	AUC (%)	Misclassification (%)	Sensitivity (%)	Specificity (%)	F-1 score (%)
Mild	LGBM	94.00	100	93.80	6.00	88.00	100	93.00
	XGBoost	93.00	100	92.80	7.00	86.00	100	92.00
	Ridge classifier	84.00	87.00	83.90	16.00	80.00	88.00	84.00
Severe	LGBM	99.00	98.00	99.00	1.00	100	98.00	99.00
	XGBoost	97.00	96.00	97.00	3.00	98.00	96.00	97.00
	Ridge classifier	89.00	88.00	89.00	11.00	90.00	88.00	89.00

AUC=Area under the receiver operating characteristic curve; LGBM=Light Gradient-Boosting Machine; XGBoost=Extreme Gradient Boosting

For future research on the application of artificial intelligence in the diagnosis of various pathologies, it is better to use all the clinical information of the patient in decision-making by the learning model. It is better to conduct future research with a larger number of subjects. Instead of manual segmentation, automatic methods including deep learning can also be used for segmentation, although these methods also have their own limitations.

## CONCLUSION

The machine learning models used in this study have significant potential to detect liver injuries caused by blunt trauma and can detect this complication in CT scan images with high accuracy and sensitivity. The ease of implementing machine learning techniques, coupled with the substantial value of the evaluation criteria obtained in this research and other studies, can convince health-care developers about the potential of these techniques to create a system for diagnosing patients with or without emergency conditions in radiology departments.

## Acknowledgments

This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Ethics Committee of Kermanshah university of medical science (IR.KUMS.MED.REC.1402.281). The authors are grateful to the Student Research Committee of Kermanshah University of Medical Sciences for supporting this project with code 4020530.

## Financial support and sponsorship

This work was supported by the Student Research Committee of Kermanshah University of Medical Sciences.

## Conflicts of interest

There are no conflicts of interest.

## REFERENCES

1. Brunicaudi FC, Andersen DK, Billiar TR, Dunn DL, Hunter JG, Matthews JB, *et al.* Schwartz's Principles of Surgery. 10<sup>th</sup> ed. New York: McGraw Hill LLC; 2014.
2. Latif RK, Clifford SP, Baker JA, Lenhardt R, Haq MZ, Huang J, *et al.* Traumatic hemorrhage and chain of survival. *Scand J Trauma Resusc Emerg Med* 2023;31:25.
3. Isenhour JL, Marx J. Advances in abdominal trauma. *Emerg Med Clin North Am* 2007;25:713-33, ix.
4. Arabzadeh A, Zandian H, Poorfarzan I, Alaei R, Haghshenas N, Ahari SS, *et al.* The frequency of laparotomy in patients with abdominal trauma: A case study of Fatemi hospital in Ardabil: 2016. *J Ardabil Univ Med Sci* 2018;18:230-9.
5. Nishijima DK, Simel DL, Wisner DH, Holmes JF. Does this adult patient have a blunt intra-abdominal injury? *JAMA* 2012;307:1517-27.
6. Remedios D, McCoubrie P, The Royal College Of Radiologists Guidelines Working Party. Making the best use of clinical radiology services: A new approach to referral guidelines. *Clin Radiol* 2007;62:919-20.

7. Expert Panel on Major Trauma Imaging, Shyu JY, Khurana B, Soto JA, Biffl WL, Camacho MA, *et al.* ACR appropriateness criteria® major blunt trauma. *J Am Coll Radiol* 2020;17:S160-74.
8. Ahmed N, Vernick JJ. Management of liver trauma in adults. *J Emerg Trauma Shock* 2011;4:114-9.
9. Badger SA, Barclay R, Campbell P, Mole DJ, Diamond T. Management of liver trauma. *World J Surg* 2009;33:2522-37.
10. Arumugam S, Al-Hassani A, El-Menyar A, Abdelrahman H, Parchani A, Peralta R, *et al.* Frequency, causes and pattern of abdominal trauma: A 4-year descriptive analysis. *J Emerg Trauma Shock* 2015;8:193-8.
11. Sepuya RG, Dozeman ET, Prittie JE, Fischetti AJ, Weltman JG. Comparing diagnostic findings and cost of whole body computed tomography to traditional diagnostic imaging in polytrauma patients. *J Vet Emerg Crit Care (San Antonio)* 2022;32:334-40.
12. Gruen RL, Jurkovich GJ, McIntyre LK, Foy HM, Maier RV. Patterns of errors contributing to trauma mortality: Lessons learned from 2,594 deaths. *Ann Surg* 2006;244:371-80.
13. Wang S, Summers RM. Machine learning and radiology. *Med Image Anal* 2012;16:933-51.
14. Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images are more than pictures, they are data. *Radiology* 2016;278:563-77.
15. Yip SS, Aerts HJ. Applications and limitations of radiomics. *Phys Med Biol* 2016;61:R150-66.
16. Sollini M, Antunovic L, Chiti A, Kirienko M. Towards clinical application of image mining: A systematic review on artificial intelligence and radiomics. *Eur J Nucl Med Mol Imaging* 2019;46:2656-72.
17. Brejnøel MW, Nielsen YW, Taubmann O, Eibenberger E, Müller FC. Artificial intelligence based detection of pneumoperitoneum on CT scans in patients presenting with acute abdominal pain: A clinical diagnostic test accuracy study. *Eur J Radiol* 2022;150:110216.
18. Farzaneh N, Stein EB, Soroushmehr R, Gryak J, Najarian K. A deep learning framework for automated detection and quantitative assessment of liver trauma. *BMC Med Imaging* 2022;22:39.
19. Colak E, H ML, Ball R, Davis M, Flanders A, Jalal S, *et al.* RSNA 2023 Abdominal Trauma Detection. Kaggle; 2023. Available from: <https://kaggle.com/competitions/rsna-2023-abdominal-trauma-detection>.
20. Laine A, Fan J. Texture classification by wavelet packet signatures. *IEEE Trans Pattern Anal Mach Intell* 1993;15:1186-91.
21. Mayerhoefer ME, Materka A, Langs G, Häggström I, Szczypiński P, Gibbs P, *et al.* Introduction to radiomics. *J Nucl Med* 2020;61:488-95.
22. Alpaydin E. Introduction to Machine Learning. Cambridge, USA: MIT press; 2020.
23. Hastie T, Tibshirani R, Friedman J. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. 2<sup>nd</sup> ed. Springer Nature One New York Plaza, New York, USA: Springer Series in Statistics; 2009.
24. Cui B, Ye Z, Zhao H, Renqing Z, Meng L, Yang Y. Used car price prediction based on the iterative framework of XGBoost+LightGBM. *Electronics* 2022;11:2932.
25. Chen T, Guestrin C, editors. Xgboost: A Scalable Tree Boosting System. Proceedings of the 22<sup>nd</sup> ACM SIGKDD International Conference on Knowledge Discovery and Data Mining; 2016.
26. Katuwal R, Suganthan PN. An ensemble of kernel ridge regression for multi-class classification. *Procedia Comput Sci* 2017;108:375-83.
27. Leape LL. Error in medicine. *JAMA* 1994;272:1851-7.
28. Waite S, Scott J, Gale B, Fuchs T, Kolla S, Reede D. Interpretive error in radiology. *AJR Am J Roentgenol* 2017;208:739-49.
29. Geyer LL, Körner M, Linsenmaier U, Huber-Wagner S, Kanz KG, Reiser MF, *et al.* Incidence of delayed and missed diagnoses in whole-body multidetector CT in patients with multiple injuries after trauma. *Acta Radiol* 2013;54:592-8.