Original Article

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

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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

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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.[1] The number of deaths caused by trauma worldwide is estimated to be over 5 million annually.[2] 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.[3] 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.[4] This kind of trauma is a significant diagnostic challenge in most cases. Patients with severe injuries and continuous bleeding need immediate identification and treatment.[5] Abdominal trauma is often not diagnosed through physical examination,

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

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.[8-10] Contrast-enhanced computed tomography (CT) is considered the gold standard technique for evaluating liver trauma and monitoring its progression over time.[9,11]

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.[12]

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.[13]

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.[14,15]

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

In a 2021 study by Brejnebøl *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%.[17]

Both early detection and severity assessment of liver trauma are critical for optimal triage and treatment of trauma patients.[18] 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[19] 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.[20] 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.[21]

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

LGBM	XGBoost	Ridge classifier
First order Median (HLH) Mean (HLH) 90 Percentile (o) Kurtosis (o(Mean (HLL) Median (LHL) Mean Absolute Deviation (o) 10 Percentile (LLH)	First order 10 Percentile (LLH) Robust Mean Absolute Deviation (LLH) 10 Percentile (LHL) 90 Percentile (LHL) Root Mean Squared (HLL) Root Mean Squared (LLL) Variance (LLL) 90 Percentile (o) 10 Percentile (o) Kurtosis (o) 10 Percentile (LLH)	First order Energy (HLL) Total Energy (HLL)
GLCM Cluster Tendency (o) IMC1 (o) IMC2 (HLL)- IMC2 (o) Sum Entropy (o)	GLCM IMC2 (o) Joint Energy (LHH) IMC1 (HHL) Difference Variance (LLL) Sum Entropy (LLL) Cluster Tendency (o) Sum Entropy (o) Autocorrelation (LLL) Inverse Variance (LLL)	
GLDM Small Dependence Emphasis (LHL) Dependence Entropy (o) Dependence Variance (o) Dependence Entropy (LLL) Large Dependence High Gray Level Emphasis (LLL) Large Dependence Low Gray Level Emphasis (LLL) Dependence Nonuniformity Normalized (o)	GLDM Small Dependence Emphasis (HLL) Dependence Entropy (o) Dependence Variance (HLH)	
GLRLM Run Entropy (LLH) Run Entropy (o) Gray Level Nonuniformity Normalized (o)	GLRLM Run Entropy (o) Gray Level Nonuniformity Normalized (o) Gray Level Nonuniformity Normalized (LLH) Short-Run Emphasis (LHH) Short-Run Emphasis (LLL)	
	GLSZM Zone Entropy (LHL) Size Zone Nonuniformity (HLL) Small Area Low Gray Level Emphasis (HLL)	GLSZM Large Area Emphasis (o) Zone Variance (o) 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.[22,23] 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.[13] 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.[24]

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.[24,25]

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.[26]

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.[21,24]

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.[8] 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.[9] 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.[27,28] 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.[29]

Table 3: Confusion matrix for mild and severe liver injury

	Mild liver injury	
Model	**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)
	Severe liver injury	
Model	**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

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.[18] 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 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.

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Conflicts of interest
There are no conflicts of interest.

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