International Surgery Journal
Kapoor A et al. Int Surg J. 2025 Apr;12(4):555-561
http://www.ijsurgery.com
pISSN 2349-3305 | eISSN 2349-2902

DOI: https://dx.doi.org/10.18203/2349-2902.isj20250814

Original Research Article

Artificial intelligence-based detection of pre-operative surgical difficulty in laparoscopic cholecystectomy patients using gradient based model

Atul Kapoor[1]*, Bholla Singh Sidhu[2], Jasdeep Singh[3]

[1]Department of Radiology, Advanced Diagnostics, Amritsar, Punjab, India
[2]Department of Surgery, Parwati Hospital Amritsar, Punjab, India
[3]Department of Surgery, Sukh Sagar Hospital, Amritsar, Punjab, India

Received: 20 December 2024
Revised: 19 February 2025
Accepted: 01 March 2025

***Correspondence:**
Dr. Atul Kapoor,
E-mail: info.advanceddiagnostics@gmail.com

ABSTRACT

Background: This study aimed to develop a gradient-based machine learning model to detect and assess potential challenges in laparoscopic cholecystectomy procedures.
Methods: This prospective study included 146 patients diagnosed with gallstones or long-term gallbladder inflammation. Ultrasound imaging and shear wave elastography were used to evaluate various factors including gallbladder location, wall thickness, stone size, cystic duct length, common bile duct, adhesions and complications. Patients were categorized into three groups based on surgical difficulty using a manual model (MM) and a machine learning (ML) model. The ML model utilized a gradient boost algorithm and was trained, validated and tested using patient data. Laparoscopic gallbladder removal was performed and the surgeon evaluated the difficulty and complications of the procedure. Statistical analyses, including parametric measures, correlation analyses and diagnostic analyses of both models, were conducted.
Results: Pericholecystic adhesions were the primary contributing factor to challenging laparoscopic cholecystectomies. The ML model achieved high accuracy (90%) for predicting preoperative surgical difficulty, with an area under the curve (AUC) of 1.0, for groups A and C and 0.89 for group B. Adhesion and cystic duct length were identified as the most significant factors in the ML model.
Conclusions: The study concluded that the application of machine learning, specifically the Gradient Boosting Machine (GBM) model, enhanced the results of the manual model and demonstrated superior precision in predicting preoperative surgical difficulty.

Keywords: Laparoscopic cholecystectomy, Pericholecystic adhesion, Shear wave elastography, Ultrasonography

INTRODUCTION

Machine learning has revolutionized various fields, including healthcare and surgical planning.[1] These applications range from order scheduling and triage to clinical decision support systems, detection and interpretation of findings and radiology reporting by Choy et al.[2] The integration of artificial intelligence (AI) and machine learning (ML) in radiology has the potential to improve diagnostic accuracy, enhance workflow efficiency and provide valuable insights for patient care.[3,4] Predicting preoperative surgical difficulty in laparoscopic cholecystectomy (LC) is crucial for optimizing patient outcomes and resource allocation and identifying the potential challenges and risks associated with the procedure.[5]

Several studies have highlighted the key factors that can predict difficulties during LC.[6,7] Important preoperative factors to assess include gallbladder wall thickness, presence of adhesions, stone size and number and the anatomy of the biliary system. Owing to the complex interplay of these factors, it is difficult to accurately predict potential surgical challenges and complications preoperatively.[6] Since most of these findings involve radiological assessment, it would be prudent to apply new imaging techniques along with machine learning algorithms to solve this conundrum of predicting surgical difficulty.[8,9]

This study introduced a gradient-based machine learning model to detect and assess potential challenges in laparoscopic cholecystectomy procedures. Gradient-based models, which are a subset of artificial intelligence algorithms, utilize the principles of gradient descent to iteratively optimize model parameters by reducing the error in the previous weak model until the time error is minimized.[10,11]

These models are particularly effective in handling complex, nonlinear relationships within data, making them suitable for analyzing the multifaceted factors that contribute to surgical difficulty. The proposed approach aimed to leverage patient-specific data, including imaging findings, clinical parameters and historical outcomes, to create a predictive model. By employing a gradient-based learning algorithm, the model can adapt and refine its predictions based on subtle patterns and correlations present in the dataset.

This introduction sets the stage for exploring how artificial intelligence, specifically gradient-based machine learning models, can be applied to enhance preoperative assessment in LC and the implications of this innovative approach for surgical planning and patient care.

METHODS

This prospective study examined 146 patients diagnosed with gallstones or long-term gallbladder inflammation who presented with upper abdominal pain, digestive issues and vomiting, as verified by ultrasound imaging at our institute over a one-year period from December 2023 to October 2024. Approval for this study was obtained from the local ethics and institutional review committee (AERB 02052024). Informed consent was obtained from all the patients.

Inclusion criteria

The inclusion Criteria were as all patients had a history of recurrent or acute pain in the right hypochondrium, persistent epigastric discomfort, vomiting or a prior history of cholelithiasis planning for surgery.

Exclusion criteria

Exclusion criteria included comorbidities, such as congestive heart failure, bleeding disorder, decompensated cirrhosis, uncontrolled diabetes or any contraindication for prospective surgery.

Assessments were performed on empty stomachs using a siemens sequoia ultrasound system with a 5C1 probe following a set abdominal evaluation protocol for the upper abdomen, followed by 2D shear wave elastography for the gallbladder wall and surrounding area along the neck and Calot triangle region.

The focus was on a) gallbladder location, b) wall thickness, c) stone size, d) cystic duct length, e) common bile duct, f) adhesions near the fundus, body, neck and Calot's triangle of the gallbladder and g) complications, such as abscesses, empyema or wall necrosis.

Shear wave elastography was conducted with patients lying on their back or left side, capturing images in the axial and oblique sagittal planes of the gallbladder. The region of interest (ROI) was centrally placed in the gallbladder and circular measurements were performed to quantify the stiffness of the area.

Ten healthy individuals with normal gallbladder walls and cavities were examined in this study. The average stiffness values of the gallbladder wall and the surrounding area were obtained with a 95% confidence interval (Figure 1).

Each of the five variables mentioned above was scored from 0 to 3 and the total score was calculated using a manual model (MM). The patients were then categorized into three groups: Group A (easy), Group B (moderately difficult) and Group C (highly difficult with complication risks) (Table 1).

A machine learning (ML) model using a gradient boost was also developed using data from 99 patients for training, 10 for validation and 25 for testing. Five variables were selected: gallbladder distension, adhesions, cystic duct length, stone size and wall thickness. The model was subjected to 100 iterations until the lowest stable trial of the error curve was reached. The highest accuracy with the lowest MSE was selected. All patients underwent laparoscopic gallbladder removal and the surgeon evaluated the difficulty and complications of the procedure (Table 2).

Based on these observations, each patient was assigned to one of the three groups, A-C, with group C representing the most challenging cases.

Statistical analysis

Statistical analysis included parametric measures, such as mean age and standard deviation. Pearson's correlation analysis with scatter plots and regression analyses was conducted for each imaging parameter. The data were evaluated for diagnostic analysis of both manual and machine learning (ML) models using GBM. The sensitivity, specificity, accuracy and area under the curve (AUC) were determined for both models and the results were compared.

RESULTS

This study examined 146 individuals suspected of cholelithiasis who underwent abdominal sonography for potential gallbladder problems during a one-year period from December 2023 to October 2024. All patients who underwent laparoscopic cholecystectomy were included after obtaining approval from the local ethics board and patient consent. Patient demographics are shown in (Table 3). The investigation identified four statistically significant variables with box plot distributions across the three groups, as illustrated in (Figure 2). Significant variations in adhesion stiffness values were noted among all groups (p<0.0001). Pearson's correlation coefficient analysis of all variables revealed statistically significant correlations among the three variables (Table 4).

The distribution of patients across groups was group B had the largest number of patients 70 (Figure 3), while 42 were in group C and 34 in group A. Group C exhibited statistically significant sex disparities (p<0.001), with females being more prevalent. For surgically challenging cases (Group C), the manual model using a cutoff score of 6 and above demonstrated 88.4%, 88.5%, 94.8% and 76% sensitivity, specificity, negative and positive predictive values, respectively, with an accuracy of 88.4% and AUC of 0.90 (Table 5).

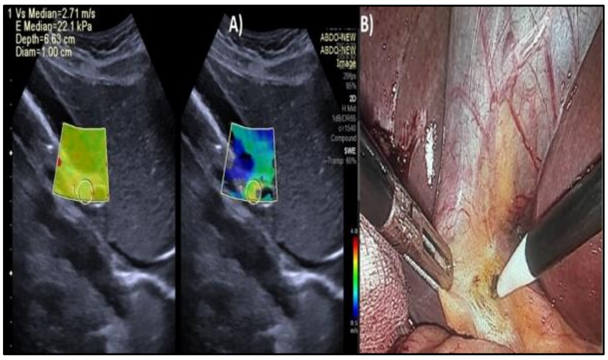

Figure 1 (A): SWE imaging showing increased stiffness 22.1 kPa at the neck. (B): Laparoscopic image showing no significant adhesion.

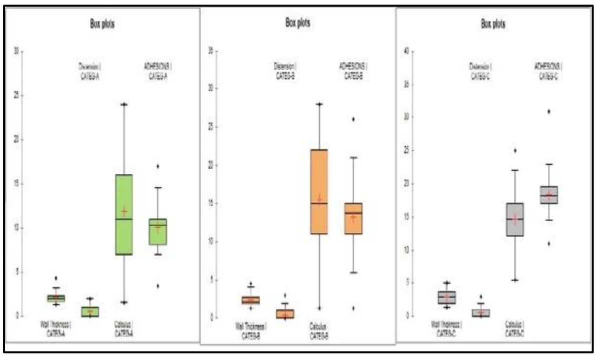

Figure 2: Box plots showing the distribution of imaging parameters among the three groups.

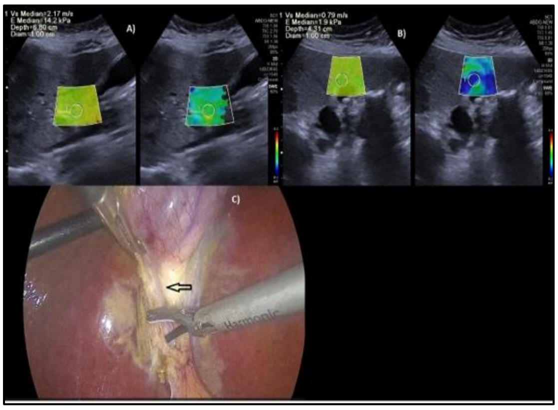

Figure 3 (A, B): SWE image of the gallbladder showing increased stiffness 14.2Kpa at the neck with no adhesions at the fundus -1.9 kPa. (C) Operative image showing adhesions at neck (arrow) in group B patient.

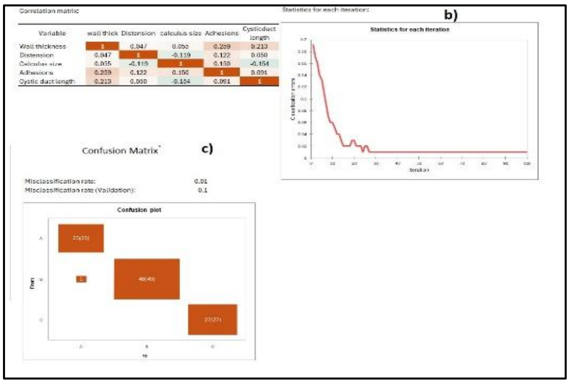

Figure 4. a) Correlation matrix of the ML model b) Iteration curve of the ML model showing reduced error after 30 iterations. c) Confusion matrix with a reduced misclassification rate of 0.01 and 0.1.

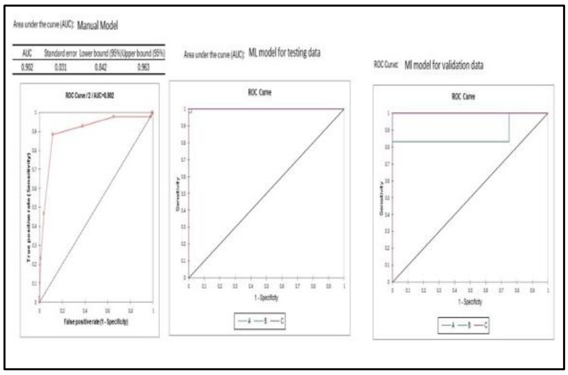

Figure 5: Comparison of the AUC values of the two models.

The machine learning model employed a gradient boosting machine (GBM) stabilized at 30 iterations, with a misclassification rate of 0.01 in the training set and 0.10 for the validation data. The correlation matrix indicated the maximum weightage of the adhesion variable with the highest variable importance of 0.48 (Figure 4). The ML model achieved 100% accuracy for groups A and C, with an AUC score of 1.0 and an AUC score of 0.89 for group B, with an overall AUC of 0.90 (Figure 5). The ML model demonstrated 90%, 85%, 74% and 100% sensitivity, specificity and positive and negative predictive values, respectively, with an accuracy of 90% (Table 5).

Table 1: Pre-laparoscopic assessment score (PLAS).

S. No.	Property	0	1	2	3
1	**Distension**	Normal	Partially distended	Not distended	Collapsed
2	**Wall thickness**	0	2.5-4	>4mm	
3	**Calculus Size**	<10 mm	10-20 mm	>20 mm	
4	**Adhesion (kPa)**	<12	12 to 15	15-18	>18
5	**Cystic duct**	20 mm	<20 mm	Not Visualised	
6	**Gall bladder complication**	Nil	Acute inflammation	Collection	Perfusion/Gangerene
7	**Congenital anomaly**	Absent	Minor abnormality/ shape	Location/ duplication	

Table 2: Operative surgical difficulty score.

	Group A (0-3 Score)	Group B (4-5 Score)	Group C (>5 score)
Procedure time	<40 Minutes	<60 Minutes	>1 Hour
Gall bladder	Distended, floppy, non-adherent	Partially distended or Mucocele, Packed with stones	Deep fossa, acute cholecystitis, gangrene, collections Contracted, Impacted neck calculus
Cystic pedicle	Thin and clear	Fat laden	not identified or with abnormal anatomy or cystic duct-short, dilated or obscured
Adhesions	Insignificant or minor up to the neck/Hartmann's pouch	Up to the body	Dense adhesions or up to fundus or involving hepatic flexure or duodenum which is difficult to identify

Table 3: Demographics and radiological parameters of the study group.

S. no.	Parameter	Group A (n=34)	Group B (n=70)	Group C (n=42)	P value
		Mean			
1	**Age**	56.5	53.4	54.4	>0.15
2	**Sex**				
	Females	17	28	31*	>0.21
	Males	17	42	11	<0.001*
3	**BMI**	27.4	26.5	27.8	<0.24
4	**Symptoms**				
	Pain abdomen	23	68	69	
	Vomiting	20	38	14	
	Dyspepsia	30	37	23	
5	**Wall thickness**	2.2 mm	2.9 mm	4.1 mm	
6	**Normal Distension**	90%	82%	73%	
7	**Cystic duct length**	23 mm	21 mm	20.5 mm	
8	**Adhesion/stiffness**	9.8 Kpa	14.8 Kpa	19.2 Kpa	<0.0001
9	**Complications**	x	7%	10%	
10	**Stone size**	8.2 mm	10.4mm	13.1 mm	0.05
11	**Comorbidities**	15%	18%	16%	0.15
12	**Blanket Sign**	6	24	18	<0.05
13	**Complications**	1%	2%	2%	

*Clinically significant

Table 4: Spearman correlation between imaging variables.

Variables	Wall thickness	Distension	Calculus	Adhesions	Cystic length	Total score
Wall thickness	0	0.011	0.784	0.002	0.706	0.001
Distension	0.011	0	0.011	0.178	0.932	0.439
Calculus	0.784	0.011	0	0.032	0.12	0.007
Adhesions	0.002	0.178	0.032	0	0.285	<0.0001
Cystic length	0.706	0.932	0.12	0.285	0	0.293
Total score	0.001	0.439	0.007	<0.0001	0.293	0

Table 5: Diagnostic analysis of manual and ML models.

Statistic	Manual model			ML model		
	Value	95% CI		Value	95% CI	
Correct classification	0.88	0.75	0.95	0.9	0.66	0.96
Misclassification	0.12	0.67	0.17	0.1	0.04	0.34
Sensitivity	0.883	0.805	0.933	1	0.55	1
Specificity	0.76	0.624	0.858	0.85	0.53	0.89
PPV (positive predictive value)	0.76	0.624	0.858	0.74	0.25	0.84
NPV (negative predictive value)	0.948	0.88	0.98	1	1	1

DISCUSSION

Pericholecystic adhesions are the primary factors contributing to challenging laparoscopic cholecystectomies, conversions to open procedures and various iatrogenic complications that classify the surgery as "Difficult".[12-14] Our research revealed that 76% (112/146) of patients in group B exhibited pericholecystic adhesions, while 28% of patients in group C had highly challenging adhesions due to their density. These findings align with the incidence rates reported by Singh et al and Yetkin et al, which were 21.5% and 17.5%, respectively.[12,13] We developed two models incorporating variables such as cholecystic adhesions on elastography, gallbladder wall thickness, stone size, cystic duct length and gallbladder distension to predict the preoperative difficulty levels.

Both models demonstrated high accuracy (88% and 90%, respectively) for group C patients, which is crucial for laparoscopic surgeons. The machine learning (ML) model achieved an Area Under the Curve (AUC) of 1.0, with a minimal misclassification rate of 0.10 in validation data. False positive classifications likely resulted from experienced surgeons' enhanced skills or cases where detected adhesions were not extensive enough to be labeled as difficult. Correlation matrix analysis identified adhesions as the most significant factor, followed by the cystic duct length. These novel determinants of difficulty have not been reported previously in the literature. Other studies typically relied on indirect indicators of difficulty, assuming associations between chronic inflammation and challenging dissection.[17-20]

Most previously proposed scoring models, such as those by Randhawa et al, Tokyo G18, Teerawiwatchai et al, model and the Labbad-Vivas’s score (LVS) model, achieved less sensitivity and AUC than both of our models and were based on a multitude of indirect factors, such as the one by Vivek et al, which had 22 variables that are difficult to fulfill in daily practice.[21-25]

Some large studies, such as those by Singh et al, were retrospective and based only on operative findings.[15] Hence, new parameters are required. To date, most studies, such as those by Chhapria et al, have suggested a wall thickening of more than 3 mm, while others, such as Naito et al, as 6.1 mm as a single key variable.[22,26] Studies by Islam et al, emphasized the presence of inflammation and correlated it with a history of colic lasting>4 days as a key predictor for difficult LC, similar to the findings of Singh et al.[15,27]

Ramakrishna et al, none the less stressed on high BMI>27 Kg//m2 as key determinant of difficulty but with all these variables predictive values were not optimal.[28] AI has recently been used in surgical videos to develop a machine-learning model for predicting operative difficulty.[29]

Our study clearly demonstrates that both manual and ML scoring methods combining adhesion detection with two statistical ultrasound parameters of wall thickness and distension have 93% and 86% sensitivity and specificity with a negative predictive value of 98% for preoperative difficulty prediction of LC, which are valuable to the surgeon in not only identifying difficult LC cases preoperatively but also in ruling out difficult cases due to high negative predictive values.

The current study also showed that the addition of ML to the GBM model further improved the prediction levels and this effect was observed in group C, that is, the most difficult patients. More than 100% specificity of the model is also important, as it gives confidence to the surgeon by ruling the difficulty level of LC.

CONCLUSION

The application of machine learning, specifically the Gradient Boosting Machine (GBM) model, enhanced the results of the manual model using imaging parameters from routine sonography and shear wave elastography.

Adhesion and cystic duct length were found to be the most significant factors in the ML model. Both manual and ML models demonstrated high accuracy in predicting preoperative surgical difficulty, with the latter showing superior precision.

Funding: No funding sources
Conflict of interest: None declared
Ethical approval: The study was approved by the Institutional Ethics Committee

REFERENCES

1. Merkin A, Medvedev ON, Krishnamurthi R. Machine learning, artificial intelligence and dementia can predict current opinions in psychiatry. 2021;35(2);123–9.
2. Xie CY, Pang CL, Chan B, Wong EY, Dou Q, Vardhanabhuti V. Machine learning and radiomics applications in esophageal cancers using non-invasive imaging methods—a critical review of literature. Cancers. 2021;13(10):2469.
3. Kocak B. Key concepts, common pitfalls and best practices in artificial intelligence and machine learning: focus on radiomics. Diagn and Interventional Radiol. 2022;28(5):450–62.
4. Handelman GS, Asadi H, Chandra RV, Brooks, et al. Peering into the black box of artificial intelligence: evaluation metrics of machine learning methods. American J Roentgenol. 2018;212(1),38–43.
5. Buono G, Romano G, Galia M, Amato G, Maienza E, Vernuccio F, et al. Difficult laparoscopic cholecystectomy and preoperative predictive factors. Sci Rep. 2021;11(1):2559.
6. Liu CL. Factors Affecting Conversion of Laparoscopic Cholecystectomy to Open Surgery. Archives of Surg. 1996;31(1):98.
7. Lee NW, Collins J, Britt LD. Evaluation of preoperative risk factors for conversion from laparoscopic to open cholecystectomy. The American Surgeon. 2012;78(8):831–3.
8. Di Buono G, Gulotta L, Maienza E. Difficult laparoscopic cholecystectomy and preoperative predictive factors. Scientific Reports. 2021;11(1):56-9.
9. Simopoulos C, Tripsianis G, Botaitis S. Risk factors for conversion from laparoscopic cholecystectomy to open cholecystectomy. Surg Endosc. 2005;19(7):905–9.
10. Mustapha A, Ali K, Mohamed L. An Overview of Gradient Descent Algorithm Optimization in Machine Learning: Application in the Ophthalmology Field. 2020: 349–359.
11. Zhou X, Gao Y, Li C, Huang Z. A multiple gradient descent design for multi-task learning on edge computing: Multi-objective machine learning approach. IEEE Transactions on Network Science and Engineering. 2021;9(1):121-33.
12. Singh K, Ohri A. Laparoscopic cholecystectomy-is there a need to convert? J Minim Access Surg. 2005;1:59–62.
13. Yetkin G, Uludag M, Citgez B, Akgun I, Karakoc S. Predictive factors for conversion of laparoscopic cholecystectomy in patients with acute cholecystitis. Bratisl Lek Listy. 2009;110:688–91.
14. Dinkel HP, Kraus S, Heimbucher J, Moll R, Knüpffer J, Gassel HJ, et al. Sonography for selecting candidates for laparoscopic cholecystectomy: A prospective study. AJR Am J Roentgenol. 2000;174:1433–9.
15. Singh K, Ohri A. Laparoscopic cholecystectomy-is there a need to convert? J Minim Access Surg. 2005;1:59–62.
16. Yetkin G, Uludag M, Citgez B, Akgun I, Karakoc S. Predictive factors for conversion of laparoscopic cholecystectomy in patients with acute cholecystitis. Bratisl Lek Listy. 2009;110:688–91
17. Dinkel HP, Kraus S, Heimbucher J, Moll R, Knüpffer J, Gassel HJ, et al. Sonography for selecting candidates for laparoscopic cholecystectomy: A prospective study. AJR Am J Roentgenol. 2000;174:1433–9.
18. Lal P, Agarwal PN, Malik VK, Chakravarti AL. A difficult laparoscopic cholecystectomy that requires conversion to an open procedure can be predicted using preoperative ultrasonography. JSLS. 2002;6:59–63
19. Corr P, Tate JJ, Lau WY, Dawson JW, Li AK. Preoperative ultrasonography to predict technical difficulties and complications in laparoscopic cholecystectomy. Am J Surg. 1994;168:54–6.
20. Ramírez-Giraldo C, Isaza-Restrepo A, Conde Monroy D, Castillo-Barbosa AC, Rubio-Avilez JJ, Van-Londoño I. What is the best score for predicting a difficult laparoscopic cholecystectomy? Diagnostic Trial Study. Int J Surg. 2023;109(7):1871-9.
21. Randhawa JS, Pujahari AK. Preoperative prediction of difficult lap chole: A scoring method. Indian J Surg. 2009;71(4):198-201.
22. Naito K, Suda K, Shinoda K, Hashiba T, Sano W, Chiku T, et al. Preoperative difficulty factors in delayed laparoscopic cholecystectomy: Tokyo guidelines 2018 surgical difficulty score Analysis. Asian J Endosc Surg. 2024;17(2):13309.
23. Teerawiwatchai C, Polprative J, Rattanachueskul K, Thomtong R. Preoperative score development: predicting difficulty in elective laparoscopic cholecystectomy. J Health Sci Med Res. 2023;29;2023994.
24. Serrano-González R, Rivero Y, Hernandez-Velasquez A, Rodriguez-Rugel T. Predicting difficulty in laparoscopic cholecystectomies: an evaluation of the labbad-vivas scores and its correlation with the parkland grading scale. Cureus. 2024;16(3):56.
25. Vivek MA, Augustine AJ, Rao R. A comprehensive predictive scoring method for difficult laparoscopic cholecystectomy. Journal of Min Acc Surg. 2014;10(2):62-7.
26. Chhaparia S, Dewangan KP, Rao Geddam S.: Prediction of difficult laparoscopic cholecystectomy based on preoperative ultrasonography assessment. Int Surg J. 2023;27;11(1):75–87.
27. Islam M, Korayem, Samer S, Bessa E. Preoperative predictors of difficult early laparoscopic cholecystectomy in Egyptian patients with acute calculous cholecystitis BMC Surgery.2024;24(1):78.

28. Ramakrishna UN, Potnuri R, Sahu RK, Chavda H. A prospective study of various preoperative factors and the development of a scoring system for predicting difficult laparoscopic cholecystectomy. Asian J Med Sci. 2024;15(6):130–5.
29. Abbing Julian R, Voskens FJ, Gerats BGA, Egging RM, Milletari F, Broeders IAMJ. AI-based assessment model of surgical difficulty during early phase laparoscopic cholecystectomy. Comput Methods Biomech Biomed Eng Imaging Vis. 2023;11(4):1299–306.

Cite this article as: Kapoor A, Sidhu BS, Singh J. Artificial intelligence-based detection of pre-operative surgical difficulty in laparoscopic cholecystectomy patients using gradient based model. Int Surg J 2025;12:555-61.