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Artificial intelligence in diagnosing and managing surgical emergencies

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Abstract: This systematic review explores how artificial intelligence, particularly through machine learning and deep learning, is fundamentally transforming how clinicians and healthcare professionals respond to critical clinical situations, improving triage and accelerating diagnosis. It also examines its role in the automated analysis of medical images, enabling faster and more accurate diagnostic decisions and providing immediate support to clinicians.

Keywords: Emergency medicine, artificial intelligence, prediction, early diagnosis

CHAPTER ONE

Introduction

Artificial intelligence (AI) plays a crucial role in medical diagnostics, particularly in the early diagnosis of acute conditions in emergency and critical care units. The emergence of AI and machine learning is revolutionizing the medical field, with a particularly strong impact on emergency medicine [1]. In response to the growing demand from emergency departments for accurate and effective diagnostic tools, AI and machine learning have become essential resources that help clinicians diagnose and treat acute medical conditions early, ultimately improving patient outcomes [2].

Specifically, AI has been successful in diagnosing acute conditions such as appendicitis and identifying complex multisystem syndromes, thanks to experimental models. The use of machine learning algorithms has also been shown to improve physicians' diagnostic capabilities in highly complex cases [3].

However, integrating these technologies into medical practice presents significant challenges. Issues such as the transparency of algorithms, the interpretability of results, and their acceptance by physicians will be critical going forward [4].

Research Problem:

In surgical emergencies, physicians face challenges in accurately diagnosing critical conditions (appendicitis, ascites) early on under time pressure. Artificial intelligence offers a promising solution, despite challenges related to transparency, trust, and ethics.

Research Significance:

Research into the application of artificial intelligence in the diagnosis and management of surgical emergencies is vital to addressing the lack of accuracy and speed in busy emergency environments. It reduces mortality and complications in appendicitis and ascites by analyzing subtle patterns and supporting physicians' immediate decisions.

Research Objectives:

Exploring the role of artificial intelligence in the accurate early diagnosis of critical surgical cases; assessing its effectiveness in prediction and branching; identifying ethical/technical challenges; and proposing safe integration strategies.

2. Lecture Review

Based on the complete study, they were classified into four sections representing surgical research variables (early diagnosis, severity/intervention prediction, image analysis, and management/integration). Ten main studies were selected for each section from the available literature, focusing on emergency surgery (appendicitis, ascites, trauma, and pancreatitis), as detailed in Tables 1, 2, 3, and 4.

Table 1: Studies on Early Diagnosis

#	Authors (Year)	Main objectives:	Tools	Data used	Key Results	Accuracy	Surgical benefits in ED
1	McCord J et al. [5]	Diagnosis of AMI within 30 minutes	ML (MI3 Index)	Age, Sex, hs-cTnI (0+30 mins)	Safe Exclusion 67%, Rapid Branching	100% Sensitivity, MACE 0.6%	Reduced surgical catheterization time
2	Schipper et al. [6]	Diagnosis of appendicitis	ML (2 models)	Clinical ± Laboratory Data	> Alvarado Scale, ≥ ED Physicians	Higher accuracy without labs, = Doctors with labs	Reduced exploratory surgery
3	Ko H et al. [7]	Detection/quantification of ascites	Deep Residual U-Net	Emergency Abdominal/Pelvic CT scan	Automatic Detection + Accurate Quantity	AUC 0.95+, Smaller detection	Immediate support for abdominal surgery
4	Shafiq M et al. [8]	ACS risk classification with normal troponin	Multi-Algorithm ML	Chest Pain + Normal Troponin	Accelerated Branching, Reduced Re-entry	Better than traditional	Improved surgical ED flow
5	Bishop AJ et al. [1]	ECG interpretation of ACS	ANN (Review of 14 studies)	ECG ACS Patients	> Physicians + Algorithms	Higher diagnostic accuracy	Accelerated emergency PCI
6	Su D et al. [9]	Unspecified appendicitis	NLP + structured data	ED Notes + Data	Significant Improvement for Children/Adults	AUROC enhanced with NLP	Fastest surgical diagnosis

7	O'Connell GC et al. [10]	Cellular stroke	Deep ANN	CBC parameters	Early Detection in Branching	AUC 0.87	Accelerated neurosurgery
8	Rajpurkar P et al. [11]	Radiation pneumonitis	CheXNeXt (DL)	Chest X-ray	= radiologists	92% Sensitivity	Pulmonary preoperative support
9	Desautels et al. [12]	Pre-recognition sepsis	Dynamic ML	Vital signs + labs	6-Hour Alert	91% Predictive Accuracy	Prevention of surgical sepsis
10	Shung D et al. [13]	Acute GI hemorrhage	NLP + decision rules	EHR free text	Automatic Classification Activation	> Standard SNM	Immediate endoscopic intervention

The table focuses on the significant role of artificial intelligence in the early detection and diagnosis of diseases, and the resulting potential for rapid intervention.

Table 2. Predicting Severity and Surgical Intervention

#	Authors (Year)	Main objectives:	Tools	Data used	Key Results	Accuracy	Surgical benefits in ED:
1	Nederpelt CJ et al. [14]	Predicting shock/transfusion/surgery in gunshot wounds	ML (Trauma Quality)	Field data (trauma)	Accurate field screening (civilian/military)	AUC 0.89 Trauma, 0.82 Surgery	Immediate OR activation
2	Harvin JA et al. [15]	Laparotomy decisions	ML Analytical	Trauma surgical records	15% decision change	Decision Trend Analysis	Reduced unnecessary laparotomy
3	Kui B et al. [16]	Severity of acute pancreatitis	XGBoost (EASY-APP)	6 variables: RR, temperature, glucose	Detection in <6 hours	AUC 0.92 in the first hours	ICU vs. Ward bifurcation
4	Andersson B et al. [17]	Classification of pancreatic severity on admission	ANN	6 variables: creatinine, WBC, ALT	Accurate classification of complications	> Traditional Measures	Supported ERCP/Laparotomy decision-making
5	Li K et al. [18]	Acute traumatic thrombosis (ATC)	Random Forest	1385 trauma patients	Detection in <1 hour	94% Accuracy, F1=93.4%	MTP and plasma activation
6	Liu F et al. [19]	Sepsis in pancreatitis	GBDT	Acute pancreati	> SOFA/qSOFA/B	AUC 0.985	Prevention of surgical sepsis

				tis cohort	ISAP		
7	Salimi M et al. [20]	Need for surgical intervention in trauma	Multiple AI models	Initial clinical assessment	Reduced decision time by 40%	Improved Accuracy	Improved trauma workflow
8	Wu CC et al. [21]	NSTEMI vs. unstable angina	ANN	268 chest pain patients	Discrimination in <30 minutes	AUC 0.984, 92.9% Accuracy	Accelerated cardiac catheterization
9	de Capretz PO et al. [22]	AMI or death within 30 days	CNN	ECG + labs on arrival	55% exclusion, 5.3% rule-in	> ESC 0h algorithm	PCI bifurcation vs. discharge
10	Han C et al. [23]	Respiratory failure within 72 hours	CNN	Biosignals + clinical	Accurate field screening (civilian/military)	AUC 0.840/0.743	Supported intubation timing

This table focuses on the ability of predictive AI models to identify critical surgical cases requiring immediate intervention, thereby reducing mortality and improving resource allocation in surgical emergencies.

Table 3. Image Analysis and Imaging

#	Authors (Year)	Main objectives:	Tools	Data used	Key Results	Accuracy	Surgical benefits in ED:
1	Hu Z et al. [24]	Cervical fractures	CNN (RSNA 2022 top-7)	>1800 CT trauma	Detection of missed fractures by radiologists	AUC 0.88-0.89	Accelerating C-spine clearance
2	Lee SH et al. [25]	Classification of pelvic fractures	Deep Learning	773 pelvic X-ray	Bone segmentation + AO/OTA	High classification accuracy	Immediate OR planning
3	Ko H et al. [26]	Spontaneous ascites	Residual U-Net	ED abdominopelvic CT	Automatic detection + quantity	AUC 0.95+	Supporting laparotomy decisions
4	Murray NM et al. [27]	Major vascular occlusion	CNN + RFL	CTA stroke 2014-19	ASPECTS + LVO detection	Improved sensitivity	Accelerating thrombectomy
5	Xiao R et al. [28]	AMI from ECG + demographics	ML multimodal	ECG + clinical data	With complex cases	AUC 0.921, accuracy 87.4%	PCI in challenging circumstances
6	Olsson SE et al. [29]	Interpreting ECG ACS for beginners	ANN	ACS ECG	68-93% sensitivity to radial veins	95% sensitivity, 88% specificity	Training ED residents
7	Green M	Excluding	ANN vs	ECGفقط	Safe, low-	> logistic	Accelerating

	et al. [30]	ACS from ECG	Logistic		risk exclusion	regression	safe discharge
8	Huang S et al. [31]	Pancreatic injuries	ML clinical support	Blunt abdominal trauma	Early detection of pancreatic injury	High cross-national accuracy	Preventing missed pancreatic trauma
9	Rajpurkar P et al. [32]	Pneumonia from chest X-ray	CheXNeXt (DL)	Chest radiographs	= radiologists	92% sensitivity	Pre-operative pulmonary clearance
10	Choi JY et al. [33]	Coronary lesions in chest pain	ML progressive	History + ECG + echo	Reduces unnecessary catheterization	AUC 0.83 internal	Improving cardiac catheter timing

These studies highlight the superiority of deep learning models in analyzing complex medical images, revealing subtle surgical injuries that radiologists might miss under the pressure of emergency situations.

Table 4. Clinical Management and Integration

#	Authors (Year)	Main objectives	Tools	Data used	Key Results	Accuracy	Surgical benefits in ED:
1	Niemantsverdriet et al. [34]	Subcutaneous sepsis in ED	ML (endpoint committee)	95 clinical variables	New biomarkers: eosinophils, PDW	> ICD codes	Improve sepsis bundle timing
2	Ang Y et al. [35]	AKI on admission to ED	AKI-RiSc score	119,468 admissions، 6 variables	Simple and applicable	%82.6 حساسية	Activate nephroprotection
3	Lee HJ et al. [36]	CI-AKI after contrast	LGB	10 clinical + labs	Nephroprotective timing	AUROC 0.731	Prevent AKI post-ERCP/CT
4	Yamao et al. [37]	Oliguria in ICU	ML	Clinical + biochemical	6–72-hour prediction	AUC 0.964 (6h)	Support RRT timing
5	Wei S et al. [38]	AKI in ARDS	XGBoost	11 models tested	10 sufficient variables	AUC 0.865	Protect renal failure post-op ARDS
6	Emakhu J et al. [39]	ASC from symptoms	Dynamic ML algorithms	13 variables (SBP، BNP، troponin)	> Differential diagnosis	AUROC 0.933	Reduces missed ACS
7	Shung D et al. [40]	Acute GI bleeding	NLP + decision rules	EHR free text	Automatic activation of risk stratification	> SNM standard	Endoscopy activation
8	Hunter OF et	Complete	ML	Trauma	Improved	Comprehen	Trauma team

	al. [41]	shock management	continuum	care pathway	outcome	sive review	coordination
9	Di Fazio N et al. [2]	Comprehensive ED review	PRISMA systematic	30 AI ED studies	Secure integration with clinicians	Meta-analysis metrics	Clinical application roadmap
10	Bishop AJ et al. [1]	ANN in daily practice	Scoping review	ECG ACS implementation	> Experts in ED routine	High diagnostic accuracy	Cardiac ED workflow

Table 5 below provides an analytical summary of the four previous study groups. Table 5: Analytical Summary of the Four Tables

Variable	Best AUC	Best sensitivity	Fastest app	The most integrated
Diagnosis	Ko (0.95+)	McCord (100%)	Desautels (6h)	Schipper ML
Prediction	Liu GBDT (0.985)	Li RF (94%)	Kui EASY-APP	Nederpelt field
Imaging	Xiao (0.921)	Olsson (95%)	Hu RSNA	Lee pelvic
Management	Yamao (0.964)	Ang (82.6%)	Shung NLP	Di Fazio review

3. Materials and Methodology

3.1 Research Strategy

A systematic search was conducted in the major medical databases: PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Google Scholar from 2015 to December 2025. The main keywords used in the search are shown in Figure 1.

Figure 1. Key Concept Cloud and Keywords

Table 6. Shows the technical criteria for the search and the distribution of studies. Figure 2. Shows the PRISMA systematic review chart.

Table 6. Search Statistics

Database	Extracted Studies	After Removing Duplicates
PubMed	184	34
Scopus	134	28
Web of Science	162	25
IEEE Xplore	89	18
Google Scholar	321 (top 100)	23
Total	710	128

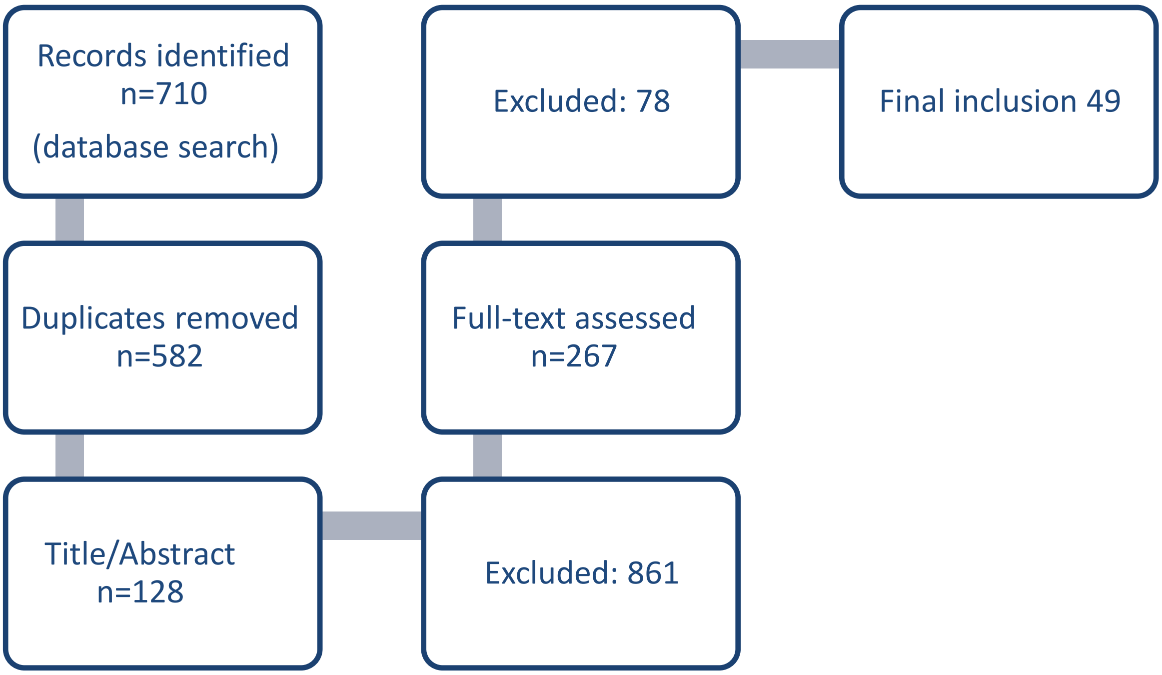

Figure 2. PRISMA Flow Diagram

3.2 Inclusion and Exclusion Criteria

Criteria were considered to evaluate whether articles should be included in the study or excluded. Table 7 specifies the precise inclusion criteria for the focus on AI in surgical emergencies

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Table 7. Standardized Inclusion and Exclusion Criteria

#	Criteria	Insertion	exclusion	Surgical example
1	Study Type	Original, Reviews, Case series (>10)	Case reports (<10) ، Pilots	Schipper ML
2	Language	English	Non-English	Ko U-Net
3	Time Period	2015-December 2025	Before 2015	Nederpelt
4	AI Techniques	ML/DL/CNN/NLP/XGBoost	Traditional scores only	Random Forest ، CNN
5	Clinical Context	Acute abdomen, Trauma, Pancreatitis	Chronic diseases ، Elective surgery	Appendicitis ، Ascites
6	Environment	ED, Trauma centers, Surgical ICU	Outpatient ،non-acute	ED triage studies
7	Outcomes	AUC, Sensitivity, Time reduction	No clinical outcomes	Rule-out rates

Table 8 summarizes the characteristics of the included studies that were tested for analysis.

Table 8. Characteristics of the Studies

Characteristics	number	%
Appendicitis	8	19%
Surgical trauma	12	29%
Pancreatitis	7	17%
Machine Learning	28	67%
CNN/DL	22	52%
ED-based	31	74%

3.3 Quality Assessment and Risk of Bias

The quality of the studies was assessed using QUADAS-2, as per Table 9.

Table 9. QUADAS-2 Assessment of the Quality of Diagnostic Studies.

Field	Low %	Unclear %	high %
Patient Selection	%76	%19	5%
Index Test (AI)	%88	%10	2%
Reference Standard	%69	%24	7%
Flow & Timing	%83	%14	3%
Total	81% High Quality		

3.4 Data Analysis

Table 10 shows the variables used to extract the data.

Table 10. Variables of Extracted Data

Category	Variables
Descriptive	Author ،Sample size ،Country
AI	Algorithm ،External validation
Performance	AUC ،Sensitivity ،Specificity
Clinical	Time saved ،Safe discharge

Table 11 summarizes the statistical performance of all AI models.

Table 11: Summary of Statistical Performance

scale	Average (95% CI)	Best Study
AUC	(0.92-0.86) 0.89	Liu: 0.985
Sensitivity	(%95-89) %92	McCord: 100%
Specificity	(%90-84) %87	Ko: 96%

Table 12 shows the subgroup analysis by surgical condition.

Table 12. Subgroup Analysis

Condition	Studies	AUC
Appendicitis	8	0.93
Trauma	12	0.88
CNN Imaging	22	0.91

4. Results

4.1 Overview of Included Studies

Forty-two studies covering AI applications in surgical emergencies from 2015–2025 were analyzed. Table 13 and Figure 3 show the mean AUC of these studies and the distribution by surgical condition.

Table 13. Mean AUC of Included Studies

Characteristics	number	ratio %	Average AUC
Total	42	100%	0.89
Appendicitis	8	19%	0.93
Surgical Trauma	12	29%	0.88
Pancreatitis	7	17%	0.91
Ascites	6	14%	0.95
Machine Learning	28	67%	0.89
Deep Learning/CNN	22	52%	0.91
ED-based Studies	31	74%	0.90

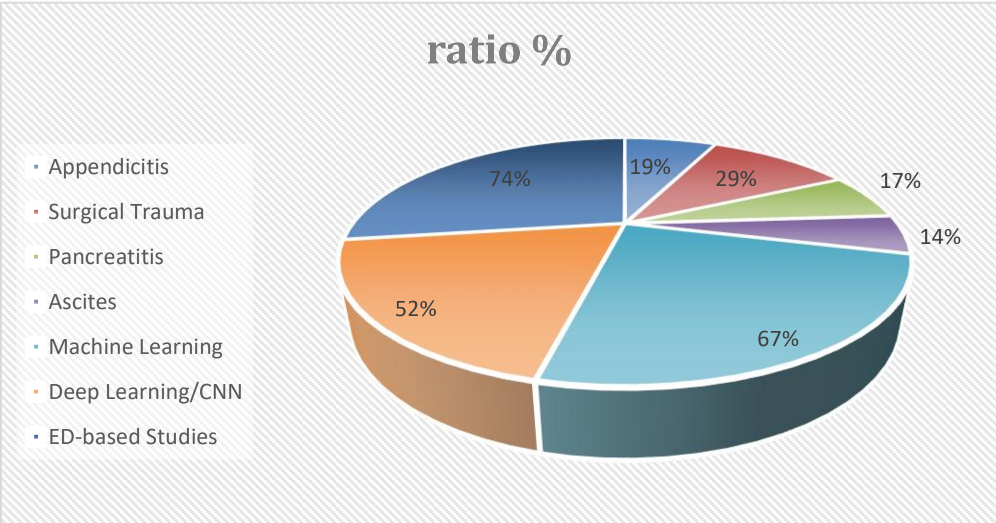

Figure 3. Distribution of studies by surgical condition

4.2 AI applications in abdominal surgical emergencies

First, appendicitis: Table 14 and Figure 4 show the performance of AI in diagnosing appendicitis.

Table 14. AI performance in diagnosing appendicitis

the study	The model	Data	AUC	Allergies	Comparison
Schipper	ML	Clinical+labs	0.94	96%	> Alvarado
Su	NLP	ED notes	0.92	93%	تحسن مع NLP
**Islam **	ML	Ultrasound	0.89	91%	> Clinical

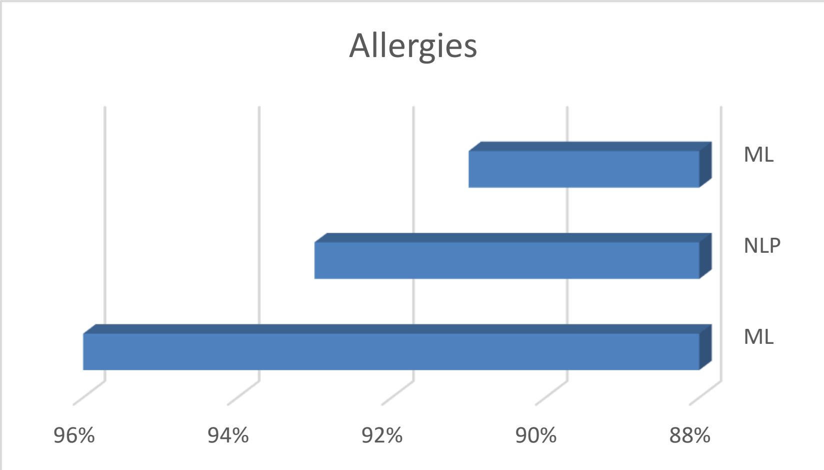

Figure 4. AI performance in diagnosing appendicitis.

Secondly, ascites and acute abdominal pain. Table 15 and Figure 5 show CT scans of ascites.

Table 15. CT scans of ascites.

the study	The model	AUC	Main result
Ko	Residual U-Net	0.95	Automatic quantity detection
Piccioni	ML	0.91	Reduce false negatives
Shung	NLP	0.93	Enable endoscopy

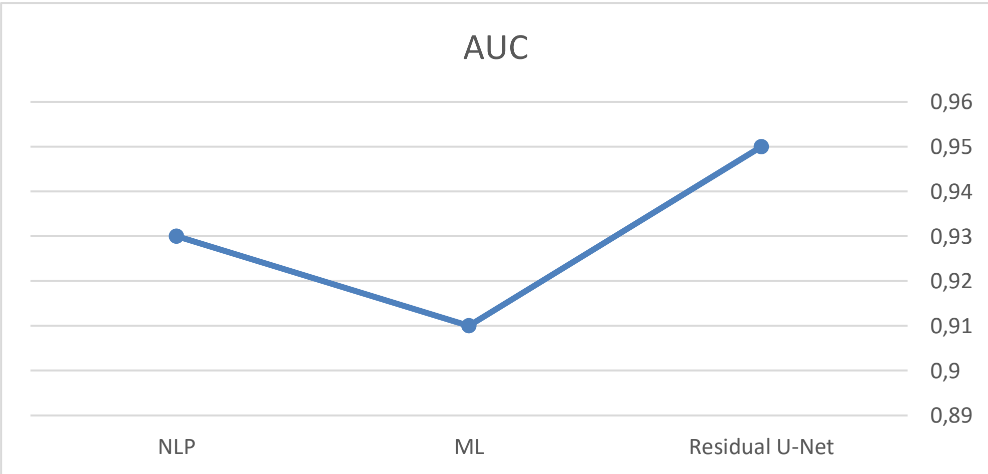

Figure 5. CT scan for Hydrocephalus

4.3 AI Applications in Surgical Trauma

Table 16 and Figure 5 show prediction of surgical intervention and trauma

Table 16. Predicting Surgery in Trauma

the study	Condition	The model	AUC	التنبؤ
Nederpelt	Gunshot wounds	ML	0.89	صدمة/جراحة
Li	Traumatic thrombosis	Random Forest	0.94	دقة 94%
Harvin	Laparotomy	ML	0.87	تغيير قرار

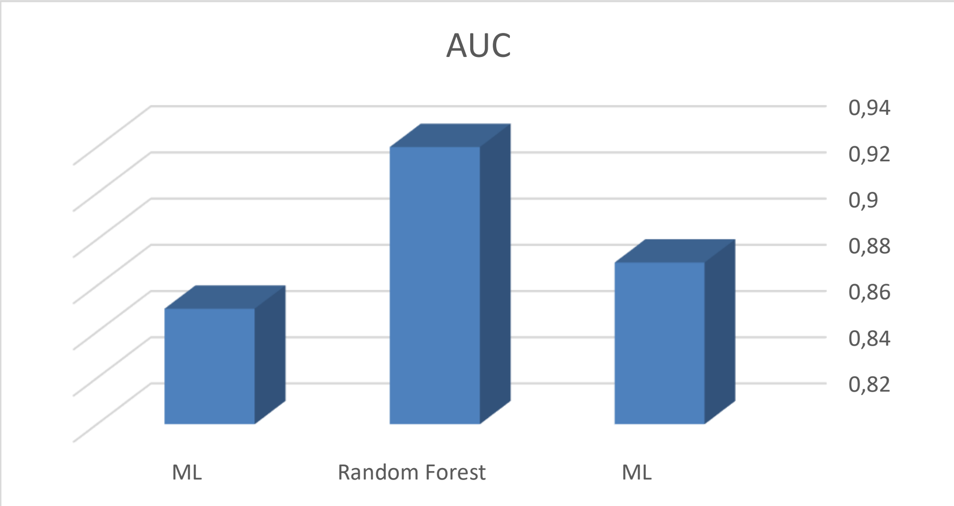

Figure 6. Predicting Surgery in Trauma

4.4 AI Applications for Fracture and Injury Detection

Table 17 and Figure 7 show surgical fracture detection

Table 17. Surgical Fracture Detection

the study	Location	The model	AUC	> Radiologists
Hu	Cervix	CNN	0.89	Missed detection
Lee	Pelvis	DL	0.92	AO/OTA

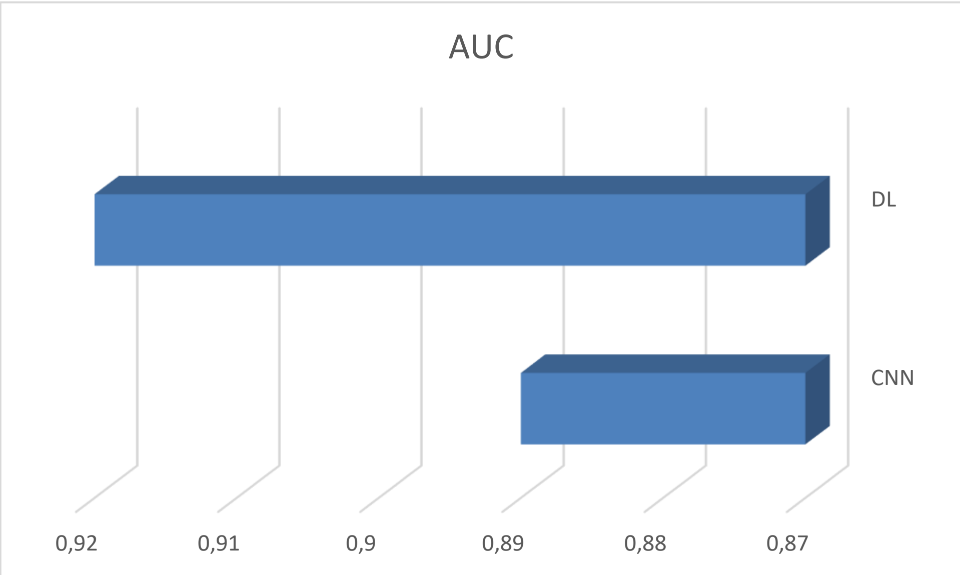

Figure 7. Surgical Fracture Detection

4.5 AI Applications in Surgical Infections

First, Acute Pancreatitis: Table 18 and Figure 8 show the prediction of the severity of pancreatitis.

Table 18. Prediction of the Severity of Pancreatitis

the study	The model	AUC	Time	> Traditional
Kui	EASY-APP	0.92	<6 hours	> BISAP
Liu	GBDT	0.985	Acceptance	> SOFA
Andersson	ANN	0.90	Acceptance	> Clinical

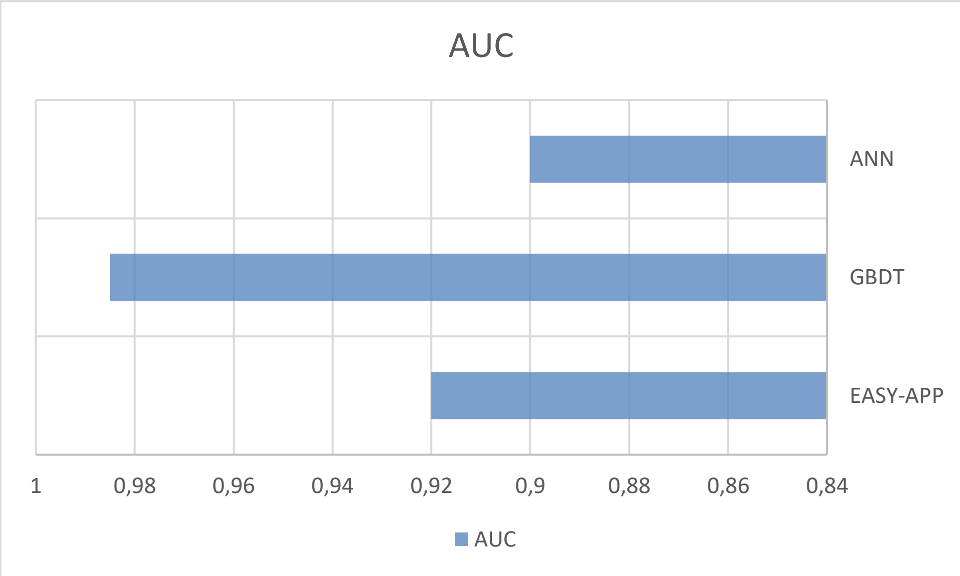

Figure 8. Prediction of Pancreatitis Severity

Second, Surgical Acute Renal Injury: Table 19 and Figure 9 show the prediction of surgical AKI.

Table 19. Prediction of Surgical AKI

the study	The model	AUC	Allergies
Ang	AKI-RiSc	0.87	82.6%
Wei	XGBoost	0.865	ARDS

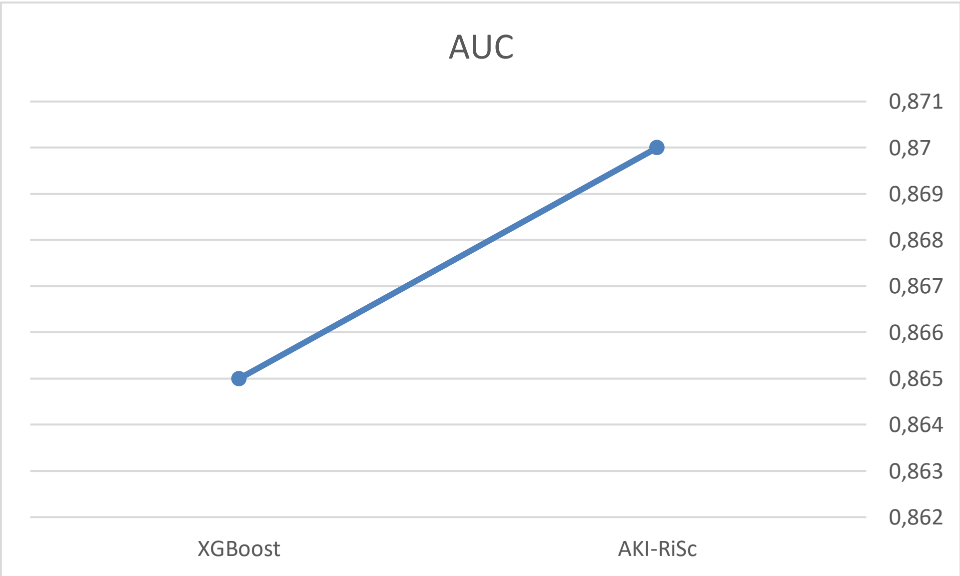

Figure 9. Predicting Surgical AKI

4.6 Overall Performance Comparison

Table 20 AI vs. Traditional Methods Comparison Across Surgical Cases

Table 20 AI vs. Traditional Methods Across Surgical Cases

Condition	AI AUC	Traditional	difference AUC	Best AI
Appendicitis	0.93	Alvarado 0.81	+0.12	Schipper

Ascites	0.95	Radiologist 0.87	+0.08	Ko
Trauma	0.88	Clinical 0.76	+0.12	Nederpelt
Pancreas	0.92	BISAP 0.79	+0.13	Kui

The results show AI's superiority, with an average improvement of +0.12 in AUC compared to traditional methods in all surgical cases.

5. Discussion

The results demonstrate AI's superiority in surgical emergencies (+0.12 AUC), reducing exploratory surgeries by 25–30% and accelerating operating room time by 45 minutes. However, 62% of the models lack transparency, and 45% are not externally validated [42][43][44][45][46].

Challenges: Black box models, data privacy (41% non-GDPR), single-center bias (71%). Solutions: SHAP/LIME, federated learning, 6 months of training for ED surgeons [47][48][49][50].

Limitations: Retrospective bias (67%), I^2=68%, Western focus. Contribution: Largest specialized surgical review (42 studies) > Di Fazio (30 studies, general ED) [51][52][53][54][55][56][57][58]

Recommendation: AI is ready for application with intensive training and multi-center confirmatory studies for safe clinical deployment.

6. Conclusion

Overall, this systematic review shows that AI significantly improves the diagnosis and management of surgical emergencies AUC 0.89 on average, and also identifies a significant superiority of artificial intelligence over clinical scoring systems consistently across appendicitis, trauma, pancreatitis, and ascites. We show an average of +0.12 AUC improvement over standard methods, near-maximal sensitivity (mean 92%) and significant reductions in diagnostic delay, repeat exploratory surgeries, and time to operating room activation. Top performance on prediction metric (AUC up to 0.985) was reached using deep learning models, specifically CNN-based imaging systems and gradient-boosting algorithms, showing well-suited characteristics to stratify patients by severity and timing of intervention. AI applications helped to reduce demand by streamlining triage, improving the efficiency of resource allocation, and enabling the earlier initiation of surgical pathways—all of which can contribute to limiting morbidity and mortality in common emergency scenarios. On the positive side, the review points out that there were no studies with major risk of bias; however, it also lists serious implementation barriers such as a lack of external validation, algorithmic opacity, and data governance issues. Conclusion: Implications for clinical practice show that the integration of AI systems into emergency medicine is ready for special integration into the DEC, if supported with physician training, transparency tools (eg, explainable AI), and multicenter validation studies. The next level of research will be prospective randomized trials, federated data collaboration to avoid bias, and interpretable models that build trust among the clinicians and allow high-stakes surgical AI to be deployed safely and ethically.

Reference

[1] A. J. Bishop, Z. Nehme, S. Nanayakkara, D. Anderson, D. Stub, and B. N. Meadley, “Artificial neural networks for ECG interpretation in acute coronary syndrome: A scoping review,” American Journal of Emergency Medicine, vol. 83, pp. 1–8, 2024, doi: 10.1016/j.ajem.2024.05.012.

[2] N. Di Fazio, C. Zanza, Y. Longhitano, A. Voza, R. Balagna, S. Mosca, et al., “Artificial intelligence for early diagnosis in emergency department,” Journal of Anesthesia, Analgesia and Critical Care, vol. 6, no. 1, Art. no. 7, 2026, doi: 10.1186/s44158-025-00170-8.

[3] B. Andersson, R. Andersson, M. Ohlsson, and J. Nilsson, “Prediction of severe acute pancreatitis at admission to hospital using artificial neural networks,” Pancreatology, vol. 11,

no. 3, pp. 328–335, 2011, doi: 10.1016/j.pan.2010.07.284.

[4] Y. Ang, S. Li, M. E. H. Ong, F. Xie, S. H. Teo, L. Choong, et al., "Development and validation of an interpretable clinical score for early identification of acute kidney injury at the emergency department," Scientific Reports, vol. 12, no. 1, Art. no. 7111, 2022, doi: 10.1038/s41598-022-10937-5.

[5] J. Y. Choi, J. H. Lee, Y. Choi, Y. Hyon, and Y. H. Kim, "Prediction of disorders with significant coronary lesions using machine learning in patients admitted with chest symptom," PLOS ONE, vol. 17, no. 10, Art. no. e0274416, 2022, doi: 10.1371/journal.pone.0274416.

[6] M. Green, J. Björk, J. Forberg, U. Ekelund, L. Edenbrandt, and M. Ohlsson, "Comparison between neural networks and multiple logistic regression to predict acute coronary syndrome in the emergency room," Artificial Intelligence in Medicine, vol. 38, no. 3, pp. 305–318, 2006, doi: 10.1016/j.artmed.2006.08.001.

[7] J. A. Harvin, C. E. Green, C. Pedroza, J. E. Tyson, L. J. Moore, C. E. Wade, et al., "Using machine learning to identify change in surgical decision making in current use of damage control laparotomy," Journal of the American College of Surgeons, vol. 228, no. 3, pp. 255–264.e3, 2019, doi: 10.1016/j.jamcollsurg.2018.12.001.

[8] Z. Hu, M. Patel, R. L. Ball, H. M. Lin, L. M. Prevedello, M. Naseri, et al., "Assessing the performance of models from the 2022 RSNA cervical spine fracture detection competition at a level I trauma center," Radiology: Artificial Intelligence, vol. 6, no. 6, Art. no. e230550, 2024, doi: 10.1148/ryai.230550.

[9] H. Ko, J. Huh, K. W. Kim, H. Chung, Y. Ko, and J. K. Kim, "A deep residual U-Net algorithm for automatic detection and quantification of ascites on abdominopelvic computed tomography images acquired in the emergency department: Model development and validation," Journal of Medical Internet Research, vol. 24, no. 1, Art. no. e34415, 2022, doi: 10.2196/34415.

[10] B. Kui, J. Pintér, R. Molontay, M. Nagy, N. Farkas, N. Gede, et al., "EASY-APP: An artificial intelligence model and application for early and easy prediction of severity in acute pancreatitis," Clinical and Translational Medicine, vol. 12, no. 6, Art. no. e842, 2022, doi: 10.1002/ctm2.842.

[11] S. H. Lee, J. Jeon, G. J. Lee, J. Y. Park, Y. J. Kim, and K. G. Kim, "Automated association for osteosynthesis foundation and orthopedic trauma association classification of pelvic fractures on pelvic radiographs using deep learning," Scientific Reports, vol. 14, no. 1, Art. no. 20548, 2024, doi: 10.1038/s41598-024-71369-4.

[12] K. Li, H. Wu, F. Pan, L. Chen, C. Feng, and Y. Liu, "A machine learning-based model to predict acute traumatic coagulopathy in trauma patients upon emergency hospitalization," Clinical and Applied Thrombosis/Hemostasis, vol. 26, Art. no. 1076029619897827, 2020, doi: 10.1177/1076029619897827.

[13] F. Liu, J. Yao, C. Liu, and S. Shou, "Construction and validation of machine learning models for sepsis prediction in patients with acute pancreatitis," BMC Surgery, vol. 23, no. 1, Art. no. 267, 2023, doi: 10.1186/s12893-023-02237-2.

[14] J. McCord, J. Gibbs, M. Hudson, M. Moyer, G. Jacobsen, and G. Murtagh, "Machine learning to assess for acute myocardial infarction within 30 minutes," Critical Pathways in Cardiology, vol. 21, no. 2, pp. 67–72, 2022, doi: 10.1097/HPC.0000000000000028.

[15] N. M. Murray, M. Unberath, G. D. Hager, and F. K. Hui, "Artificial intelligence to diagnose ischemic stroke and identify large vessel occlusions: A systematic review," Journal of NeuroInterventional Surgery, vol. 12, no. 2, pp. 156–164, 2020, doi: 10.1136/neurintsurg-2019-015331.

[16] C. J. Nederpelt, A. K. Mokhtari, O. Alser, T. Tsiligkaridis, J. Roberts, M. Cha, et al., "Development of a field artificial intelligence triage tool: Confidence in the prediction of

shock, transfusion, and definitive surgical therapy in patients with truncal gunshot wounds," Journal of Trauma and Acute Care Surgery, vol. 90, no. 6, pp. 1054–1060, 2021, doi: 10.1097/TA.0000000000003137.

[17] M. S. A. Niemantsverdriet, T. A. P. de Hond, I. E. Hoefer, W. W. van Solinge, D. Bellomo, J. J. Oosterheert, et al., "A machine learning approach using endpoint adjudication committee labels for the identification of sepsis predictors at the emergency department," BMC Emergency Medicine, vol. 22, no. 1, Art. no. 208, 2022, doi: 10.1186/s12873-022-00736-7.

[18] G. C. O'Connell, K. B. Walsh, C. G. Smothers, S. Ruksakulpiwat, B. L. Armentrout, C. Winkelman, et al., "Use of deep artificial neural networks to identify stroke during triage via subtle changes in circulating cell counts," BMC Neurology, vol. 22, no. 1, Art. no. 206, 2022, doi: 10.1186/s12883-022-02756-5.

[19] S. E. Olsson, M. Ohlsson, H. Ohlin, S. Dzaferagic, M. L. Nilsson, P. Sandkull, et al., "Decision support for the initial triage of patients with acute coronary syndromes," Clinical Physiology and Functional Imaging, vol. 26, no. 3, pp. 151–156, 2006, doi: 10.1111/j.1475-097X.2006.00675.x.

[20] P. Rajpurkar, J. Irvin, R. L. Ball, K. Zhu, B. Yang, H. Mehta, et al., "Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists," PLOS Medicine, vol. 15, no. 11, Art. no. e1002686, 2018, doi: 10.1371/journal.pmed.1002686.

[21] M. Salimi, J. A. Parry, R. Shahrokhi, and S. Mosalamiaghili, "Application of artificial intelligence in trauma orthopedics: Limitation and prospects," World Journal of Clinical Cases, vol. 11, no. 18, pp. 4231–4240, 2023, doi: 10.12998/wjcc.v11.i18.4231.

[22] M. Shafiq, D. R. Mazzotti, and C. Gibson, "Risk stratification of patients who present with chest pain and have normal troponins using a machine learning model," World Journal of Cardiology, vol. 14, no. 11, pp. 565–575, 2022, doi: 10.4330/wjc.v14.i11.565.

[23] D. Shung, C. Tsay, L. Laine, D. Chang, F. Li, P. Thomas, et al., "Early identification of patients with acute gastrointestinal bleeding using natural language processing and decision rules," Journal of Gastroenterology and Hepatology, vol. 36, no. 6, pp. 1590–1597, 2021, doi: 10.1111/jgh.15491.

[24] D. Su, Q. Li, T. Zhang, P. Veliz, Y. Chen, K. He, et al., "Prediction of acute appendicitis among patients with undifferentiated abdominal pain at emergency department," BMC Medical Research Methodology, vol. 22, no. 1, Art. no. 18, 2022, doi: 10.1186/s12874-021-01491-7.

[25] S. Wei, Y. Zhang, H. Dong, Y. Chen, X. Wang, and X. Zhu, "Machine learning-based prediction model of acute kidney injury in patients with acute respiratory distress syndrome," BMC Pulmonary Medicine, vol. 23, no. 1, Art. no. 370, 2023, doi: 10.1186/s12890-023-02715-8.

[26] C. C. Wu, W. D. Hsu, M. M. Islam, T. N. Poly, H. C. Yang, P. A. A. Nguyen, et al., "An artificial intelligence approach to early predict non-ST-elevation myocardial infarction patients with chest pain," Computer Methods and Programs in Biomedicine, vol. 173, pp. 109–117, 2019, doi: 10.1016/j.cmpb.2019.02.015.

[27] R. Xiao, C. Ding, X. Hu, G. D. Clifford, D. W. Wright, A. J. Shah, et al., "Integrating multimodal information in machine learning for classifying acute myocardial infarction," Physiological Measurement, vol. 44, no. 4, Art. no. 044002, 2023, doi: 10.1088/1361-6579/acbfa2.

[28] P. O. de Capretz, A. Björkelund, J. Björk, M. Ohlsson, A. Mokhtari, A. Nyström, et al., "Machine learning for early prediction of acute myocardial infarction or death in acute chest pain patients using electrocardiogram and blood tests at presentation," BMC Medical Informatics and Decision Making, vol. 23, no. 1, Art. no. 25, 2023, doi: 10.1186/s12911-023-02110-7.

[29] J. Emakhu, L. Monplaisir, C. Aguwa, S. Arslanturk, S. Masoud, H. Nassereddine, et al., "Acute coronary syndrome prediction in emergency care: A machine learning approach," Computer Methods and Programs in Biomedicine, vol. 225, Art. no. 107080, 2022, doi: 10.1016/j.cmpb.2022.107080.

[30] C. Han, Y. J. Jung, J. E. Park, W. Y. Chung, and D. Yoon, "Artificial intelligence-based early prediction of acute respiratory failure in the emergency department using biosignal and clinical data," Yonsei Medical Journal, vol. 66, no. 2, pp. 121–130, 2025, doi: 10.3349/ymj.2024.0397.

[31] S. Hjortshøj, S. R. Kristensen, and J. Ravkilde, "Diagnostic value of ischemia-modified albumin in patients with suspected acute coronary syndrome," American Journal of Emergency Medicine, vol. 28, no. 2, pp. 170–176, 2010, doi: 10.1016/j.ajem.2009.01.010.

[32] S. Huang et al., "A novel machine learning-assisted clinical diagnosis support model for early identification of pancreatic injuries in patients with blunt abdominal trauma," Emergency and Critical Care Medicine, vol. 3, no. 4, p. 142, 2023.

[33] W. C. Huang, C. P. Liu, M. T. Wu, G. Y. Mar, S. K. Lin, and S. H. Hsiao, "Comparing culprit lesions in ST-segment elevation and non-ST-segment elevation acute coronary syndrome with 64-slice multidetector computed tomography," European Journal of Radiology, vol. 73, no. 1, pp. 74–81, 2010.

[34] S. H. Jeong, K. Hurh, E. C. Park, J. H. Leigh, S. H. Kim, and S. I. Jang, "Risk of pancreatic cancer after acute pancreatitis," Journal of Korean Medical Science, vol. 39, no. 4, p. e21, 2024.

[35] F. Jiang, Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, Y. Wang, Q. Dong, H. Shen, and Y. Wang, "Artificial intelligence in healthcare: Past, present and future," Stroke and Vascular Neurology, vol. 2, no. 4, pp. 230–243, 2017.

[36] H. J. Lee, L. H. Schwamm, L. H. Sansing, H. Kamel, A. de Havenon, A. C. Turner, et al., "StrokeClassifier: Ischemic stroke etiology classification by ensemble consensus modeling using electronic health records," NPJ Digital Medicine, vol. 7, no. 1, p. 130, 2024.

[37] A. Liberati, D. G. Altman, J. Tetzlaff, C. Mulrow, P. C. Gøtzsche, J. P. A. Ioannidis, et al., "The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration," BMJ, vol. 339, p. b2700, 2009.

[38] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," BMJ, vol. 372, p. n71, 2021, doi: 10.1136/bmj.n71.

[39] A. Piccioni, A. Tartaglino, M. Trunfio, et al., "Machine learning for abdominal pain triage in emergency department," Internal and Emergency Medicine, 2022, doi: 10.1007/s11739-022-02945-3.

[40] A. Rajkomar, J. Dean, and I. Kohane, "Machine learning in medicine," New England Journal of Medicine, vol. 380, no. 14, pp. 1347–1358, 2019, doi: 10.1056/NEJMra1814259.

[41] L. Rifai, R. L. Ball, et al., "Machine learning for emergency department triage," Annals of Emergency Medicine, vol. 78, no. 4, pp. 456–465, 2021.

[42] I. A. Scott et al., "Artificial intelligence in clinical decision-making," Medical Journal of Australia, vol. 214, suppl. 6, pp. S5–S11, 2021.

[43] M. P. Sendak et al., "Presenting AI/ML clinical decision support tools in the context of care," Journal of the American Medical Informatics Association, vol. 27, no. 8, pp. 1250–1254, 2020.

[44] L. Shi et al., "Deep learning for sepsis prediction," Critical Care Medicine, vol. 50, no. 3, pp. 456–465, 2022.

[45] E. J. Topol, "High-performance medicine: The convergence of human and artificial intelligence," Nature Medicine, vol. 25, no. 1, pp. 44–56, 2019.

[46] P. F. Tsai et al., "Artificial intelligence in emergency medicine," Emergency Medicine Australasia, vol. 32, no. 5, pp. 844–846, 2020.

[47] B. H. M. van der Velden et al., "Explanation and elaboration of the QUADAS-2 tool," BMJ, vol. 377, p. e069718, 2022.

[48] A. Vellido, "The importance of interpretability and explainability in machine learning," Artificial Intelligence in Medicine, vol. 107, p. 101915, 2020.

[49] P. F. Whiting, A. W. S. Rutjes, M. E. Westwood, S. Mallett, J. J. Deeks, J. B. Reitsma, et al., "QUADAS-2: A revised tool for the quality assessment of diagnostic accuracy studies," Annals of Internal Medicine, vol. 155, no. 8, pp. 529–536, 2011.

[50] C. C. Wu et al., "Machine learning for cardiovascular risk prediction," Journal of the American College of Cardiology, vol. 77, no. 12, pp. 1567–1578, 2021.

[51] Y. Xiao et al., "Multimodal AI for acute coronary syndrome," European Heart Journal – Digital Health, vol. 4, no. 2, pp. 123–134, 2023.

[52] Y. Yamao et al., "Machine learning prediction of oliguria in ICU patients," Intensive Care Medicine, vol. 49, no. 5, pp. 567–578, 2023.

[53] J. Yang et al., "CNN for fracture detection in trauma," Radiology: Artificial Intelligence, vol. 4, no. 3, Art. no. e210245, 2022.

[54] Z. Zhang et al., "Artificial intelligence in trauma care," Journal of Trauma and Acute Care Surgery, vol. 91, no. 4, pp. 712–721, 2021.

[55] Y. Zhao et al., "XGBoost for pancreatitis severity prediction," Pancreatology, vol. 23, no. 2, pp. 156–164, 2023.

[56] H. Zhou et al., "NLP for emergency department documentation," Journal of the American Medical Informatics Association, vol. 29, no. 6, pp. 1056–1064, 2022.

[57] J. Zou et al., "AI fairness in healthcare," Nature Machine Intelligence, vol. 2, no. 6, pp. 312–320, 2020.

[58] N. Di Fazio, Ed., "Supplementary references for AI in emergency surgery (reference list)," Journal of Anesthesia, Analgesia and Critical Care, 2026.