**Name of Journal:** *Artificial Intelligence in Gastrointestinal Endoscopy*

**Manuscript NO:** 89138

**Manuscript Type:** MINIREVIEWS

**Artificial intelligence: Applications in critical care gastroenterology**

Juneja D. AI in critical care gastroenterology

Deven Juneja

**Deven Juneja,** Department of Critical Care Medicine, Max Super Speciality Hospital, New Delhi 110017, India

**Author contributions:** Juneja D researched the subject, performed data accusation, performed the writing and reviewed the final manuscript.

**Corresponding author: Deven Juneja, DNB, MBBS, Director,** Department of Critical Care Medicine, Max Super Speciality Hospital, 1 Press Enclave Road, Saket, New Delhi 110017, India. devenjuneja@gmail.com

**Received:** October 21, 2023

**Revised:** December 7, 2023

**Accepted:** December 26, 2023

**Published online:**

**Abstract**

Gastrointestinal (GI) complications frequently necessitate intensive care unit (ICU) admission. Additionally, critically ill patients also develop GI complications requiring further diagnostic and therapeutic interventions. However, these patients form a vulnerable group, who are at risk for developing side effects and complications. Every effort must be made to reduce invasiveness and ensure safety of interventions in ICU patients. Artificial intelligence (AI) is a rapidly evolving technology with several potential applications in healthcare settings. ICUs produce a large amount of data, which may be employed for creation of AI algorithms, and provide a lucrative opportunity for application of AI. However, the current role of AI in these patients remains limited due to lack of large-scale trials comparing the efficacy of AI with the accepted standards of care.

**Key Words:** Artificial intelligence; Critical care; Gastroenterology; Hepatology; Intensive care unit; Machine learning

Juneja D. Artificial intelligence: Applications in critical care gastroenterology. *Artif Intell Gastrointest Endosc* 2023; In press

**Core Tip:** The scope and applications of artificial intelligence (AI) are rapidly increasing. It is being increasingly applied in various fields, even in healthcare settings. The data generated by critically ill patients admitted in intensive care units (ICUs) is huge, which may be helpful in developing AI algorithms aimed to aid in their management. Patients with primary gastrointestinal diseases may frequently require ICU admission for management of advanced disease or related complications. Use of AI may aid the critical care physicians in managing such patients by helping in early diagnosis, prediction of complications, assessing response to therapy and overall prognostication.

**INTRODUCTION**

Artificial intelligence (AI), in simple terms, may be defined as the simulation of human intelligence in machines which are programmed to react like humans, mimicking their actions by means of multi-disciplinary approach[1]. Unlike human mind, which can assimilate only a finite amount of data, machines can accumulate and process unlimited amount of data which can be used in different applications. AI is increasingly influencing every aspect of our life, including healthcare[2].

AI is a complex and rapidly evolving technology. More subsets of AI are being introduced regularly, and each of them have their own unique properties, advantages and limitations. Certain subsets of AI are more commonly employed in healthcare settings than others. The broad subsets of AI include machine learning (ML), deep learning, and cognitive computing. ML involves learning from the prior data to predict the future data. Artificial neural network (ANN) is a subset of ML inspired by the neuronal connections of the human brain. Its further subsets include deep neural network and convolutional neural network (CNN). Other AI algorithms commonly employed in healthcare settings include decision trees, random forest, support vector machines (SVMs), and Naïve Bayes.

Modern intensive care units (ICUs) produce a vast amount of data which is conducive for formation of AI algorithms[2]. A significant proportion of ICU patients are admitted with gastrointestinal (GI) disease or develop GI complications during their ICU course, necessitating further diagnostic and therapeutic interventions. As these patients form a vulnerable group, prone to develop side effects and complications, all measures must be undertaken to reduce invasiveness and ensure safety of ICU procedures. AI can potentially aid the critical care physicians by helping in early diagnosis, predicting complications and response to therapy and providing clinical prognostication in several GI disorders in critically ill patients (Table 1).

**PANCREATIC DISORDERS**

Almost 25% patients with acute pancreatitis (AP) develop complications or organ failure necessitating ICU admission[3]. Severe acute pancreatitis (SAP) is associated with high morbidity and mortality, necessitating intensive monitoring and organ support. Early recognition of risk factors associated with progression to severe disease and development of complications, may help in initiating therapeutic measures and improve outcomes.

***Diagnosis***

Diagnosis of AP is based on the clinical presentation, laboratory parameters (serum amylase and lipase levels) and imaging (ultrasonography/computed tomography scans). As per the revised Atlanta classification, two out of three diagnostic criteria should be positive to make the diagnosis[4]. However, diagnosis may sometimes be missed due to non-specific clinical presentation, difficulty in imaging and low sensitivity of the revised Atlanta criteria, which may delay the treatment[5].

Integration of AI technology may aid in early diagnosis of acute pancreatitis[6]. ANNs can accurately diagnose AP using clinical and radiological data[7]. In 10%–20% of AP cases, acute necrotizing pancreatitis (ANP) develops, thus further increasing the risk of morbidity and mortality[8,9]. AI based models may also be useful in diagnosing acute necrotizing pancreatitis, which may affect treatment and prognosis[10].

***Severity prediction and assessment***

Several clinical scores, based on clinical, laboratory, and radiological risk factors, have been devised to assess severity and predict outcomes in patients with SAP. However, no single score has been proven to be superior to others and the search for an ideal scoring system continues[11]. Even though these tools are commonly used in clinical practice, they have low accuracy (60%-80%)[12]. Further, these models are complex, difficult to compute and have low specificity and positive predictive value. Moreover, some of these scoring systems, like Glasgow and Ranson scores, take 48 h to complete and are not devised for serial measurements[13].

AI tools like ANN have been utilised to develop algorithms based on routine blood and serum biochemical parameters to reliably predict severity of AP[14]. When compared to different clinical scores, ANN based models have performed better than Ranson’s, APACHE II, and modified Glasgow score in predicting severity in patients with AP[15-17]. Additionally, ANN based tools require lesser parameters and may be computed within 6 h of presentation, as opposed to some score which may require up to 48 h.

***Prediction of complications and organ failure***

Majority of deaths due to AP, especially those occurring in the first week, are secondary to progressive organ failure[18,19]. Moreover, progressive organ failure is the primary determinant of SAP, irrespective of any local pancreatic complication. Hence, it is imperative to determine patients at risk of developing organ failure and ensure an early diagnosis of any organ dysfunction. ANN based model utilising commonly employed patient and laboratory parameters have been shown to be accurately predict development of organ failure in AP patients[20].

AI based tools like regression tree algorithms and ANN have been used to predict complications such as acute lung injury, ARDS, portal vein thrombosis and porto-spleno-mesenteric vein thrombosis in patients with AP and AI has been proven to be more accurate than logistic regression based models in predicting these complications[21-25].

***Prognostication***

In spite of recent advances, mortality associated with SAP remains significant[26]. The overall mortality of ANP is approximately 15%–20%, of which there is a further twofold increase in a third of ANP cases where the necrotic tissue becomes infected[27,28]. Better understanding of risk factors associated with poorer clinical outcomes may help the physicians in instituting therapeutic measures and prognostication, as early intervention, within first 48 h, may help in improving outcomes[29].

Even though several clinical scores are commonly employed to aid in prognostication, these scores have several limitations. AI algorithms based on ANN have been shown to be better than these clinical scores in predicting clinical outcomes including length of hospital stay in patients with acute pancreatitis. Keogan *et al*[30] used ANN based on radiological and laboratory data from pancreatitis patients which performed better than both the Balthazar and Ranson scoring systems.

Data collected from acute pancreatitis patients from the Medical Information Mart for Intensive Care-III (MIMIC-III) database has shown that AI based algorithm can be effectively used to predict in-hospital mortality with an area under the curve (AUC) of 0.769. Further, AI based algorithms performed better than the commonly used scoring systems including SOFA score (AUC 0.401) and Ranson score (AUC 0.652) and logistic regression analysis (AUC 0.607) in predicting in-hospital mortality[14,31,32].

**LIVER DISORDERS**

Acute liver failure is a common indication for ICU admission. Patients with chronic liver disease (CLD) may also require ICU support in case of acute decompensation, development of acute on chronic liver disease or due to natural progression of CLD. Even ICU patients may develop liver dysfunction necessitating early diagnosis and intervention for improving prognosis. AI may have a potential role in early diagnosis of acute decompensation, identification of complications and prognostication in patients with liver disease.

***Diagnosis of CLD***

In critically ill patients, bedside ultrasonography is primarily used for diagnosis of CLD. However, it is operator dependant, qualitative in nature and have limited accuracy. Further, it may be difficult to distinguish fatty changes from early cirrhosis because of overlapping features[33]. Machine learning algorithms based on ultrasound have been applied for analysis of steatosis and the staging of liver fibrosis. Using ultrasound images, CNN based AI model has been shown to effectively assess the amount of liver steatosis with an area under the receiver operating curve (AUROC) of 0.98[34]. Deep learning-based algorithms have shown to improve accuracy for diagnosis of CLD with an AUROC of 1.0 as compared to conventional AI algorithms developed using SVM[35]. Furthermore, ML algorithms based on simple patient (age) and laboratory parameters (aspartate aminotransferase, albumin, and platelet count) have also been shown to accurately predict advanced fibrosis[36].

Liver fibrosis strongly correlates with development of hepatocellular cancer (HCC) and poor outcomes in patients with CLD. Liver biopsy remains the gold standard for detection and quantification of fibrosis. As it is an invasive procedure, it is associated with several inherent complications, especially in more vulnerable critically ill patients. Hence, non-invasive tests like bedside transient elastography measuring liver stiffness are being evaluated for such clinical conditions helping in bedside diagnosis and staging of liver fibrosis. Even though it is a comparatively a newer test, it may find better applicability in ICU patients because of its high accuracy, easy repeatability, and non-invasive nature[37]. It has been shown that, AI based on transient elastography scans may further improve its accuracy and reduce subjectivity and inter-observer variations[38,39].

As AI based tools including ANN have been shown to reliably predict significant fibrosis in patients with chronic hepatitis, AI may be helpful in accurately staging liver fibrosis and may help in reducing the need for invasive procedures like liver biopsy[40,41].

***Prediction of complications***

CLD patients are at risk of developing local and systemic complications which may sometimes be life-threatening. Among the local complications, variceal bleed remains a common cause for increased morbidity and mortality in CLD patients. Hence, prediction and prevention of variceal bleed may improve clinical outcomes. Certain clinical scores (Child-Pugh score) and clinical parameters (hepatic-venous pressure gradient) have been successfully used as prognostic factors to stratifying the risk of variceal rebleeding[42]. However, they have limited accuracy. Diagnosis of varices requires endoscopy, which may not be feasible in many critically ill patients due to its invasive nature. ANN and ML based tools have been used to accurately predict presence of esophageal varices, obliviating the need for invasive endoscopy[43,44]. AI based algorithms also have the potential to accurately predict the risk of rebleeding in patients with liver cirrhosis which may aid the clinicians in managing such patients[45].

***Prognosis***

Short term prognosis of CLD depends upon development of complications and other organ dysfunction. ICU patients with CLD have high mortality rates especially if they develop other organ dysfunction requiring renal replacement therapy or invasive mechanical ventilation support[46]. On the other hand, long term prognosis depends on disease progression. Studies have shown that AI may be instrumental in identifying the cirrhotic patients at risk for disease progression and development of liver related complications including HCC, death, hepatic decompensation and even need for liver transplantation[47,48]. In CLD patients, DL-based model has been shown to be a good predictor of transplant-free survival at 1 and 3 years after diagnosis[48].ANN algorithms based on clinical and laboratory parameters has been shown to accurately predict 1 year mortality in patients with CLD. This may aid in patient selection for liver transplantation[49].

Development of HCC may also impact clinical outcomes in such patients. ML has been employed for predicting development of HCC, diagnosis of HCC and even prediction of response to therapy[50-52].

AI may also be helpful in diagnosing focal liver lesions. AI based tools have shown to be useful in diagnosing and classifying liver nodules (cysts, hemangiomas, HCC) using ultrasound images[53,54]. DL and CNN based algorithms using MRI images, have also been shown to be effective in differentiating benign and malignant liver tumors, and classifying HCC and other tumors[55,56].

***Response to therapy***

In patients with liver disease it may be useful to identify patients who may respond to therapeutic interventions. This may aid in patient prognostication and triaging of limited ICU resources. ANN based models have been used to accurately predict the response to therapy with pegylated interferon alpha and ribavirin in patients with chronic hepatitis C infection, with sensitivity and specificity approaching 90%[57]. AI may also aid in predicting outcomes and risk for complications in post-liver transplantation patients[58].

**INTESTINAL DISORDERS**

Endoscopy is frequently employed to evaluate the gastro-intestinal tract. As it is an invasive procedure, it may be difficult to perform and associated with significant complication rates especially in critically ill ICU patients[59].

***Diagnosis***

Diagnosis of common GI disorders can be aided with AI based technology. ANN based model has been shown to reliably diagnose gastroesophageal reflux disease non-invasively by employing only clinical parameters[60]. CNN model based on endoscopic images has been shown to accurately diagnose Helicobacter pylori infection. Further, it was shown that the time required by AI to analyze the endoscopy images and make a diagnosis was significantly less as compared to experienced endoscopists (3 min and 14 s *vs* 230.1 min)[61]. Even a recently published meta-analysis reported that CNN may be as accurate as experienced physicians in making the diagnosis of Helicobacter pylori infection[62].

AI based algorithms have been developed to diagnose and differentiate between malignant and non-malignant esophageal diseases like Barret’s esophagus and squamous cell carcinoma[63]. Moreover, AI may even be helpful in identifying early neoplastic changes to ensure timely diagnosis which may enable early intervention and aid in improving outcomes[64].

***Gastrointestinal bleed***

GI bleed remains a common indication for ICU admission. Additionally, increased stress, use of steroids and presence of sepsis can predispose general ICU patients to develop GI bleed during their ICU course. Some bleeds, especially those involving the small bowel, may be difficult to identify and manage. Even though the causes for upper and lower GI bleed may be relatively easier to identify using endoscopic techniques, repeated endoscopies may be required in a significant proportion of patients at risk for recurrent bleed. This may be especially difficult in critically ill ICU patients, who may benefit most from such procedures. ML based algorithms using endoscopic images have been developed which may be useful in identifying the patients at risk of rebleed and increased mortality with up to 90% accuracy[65-68]. ML models based only on clinical parameters like age, presence of gastric ulcers or gastrointestinal disease, presence of underlying malignancy or infections and serum hemoglobin levels have also been developed which has shown to predict risk of rebleed up to 1 year with an accuracy of 84.3% which may obliviate the need for repeated bronchoscopies[69].

AI, using various algorithms, have been shown to be helpful in more accurately identifying the source of bleed in patients with small bowel bleed using images from capsule endoscopy, which may avoid further invasive tests[70-73].

Hence, AI have the potential to reduce the need for endoscopies, allow for quicker procedures (by shortening the time required for observation and analysis), and also decrease the necessity for performing endoscopic biopsies, which may be particularly beneficial for critically ill patients.

**BILIARY DISORDERS**

Endoscopic retrograde cholangiopancreatography (ERCP) is commonly employed to diagnose disorders of the gall bladder, bile duct and the pancreas. However, it may be difficult to perform and may be associated with significant complications. Hence, careful patient selection is of paramount importance. An ANN model has been shown to have better discriminant ability and accuracy than a multivariate logistic regression model in selecting patients for therapeutic ERCP[74]. Using data collected from endoscopic images, AI has also been used to predict difficult ERCP which may help in reducing the failure rates and performing safer procedures[75,76]. AI model based only on clinical markers has been shown be an important adjunct to more invasive procedures in evaluation of bile duct obstruction[77].

AI may also support the physicians performing the ERCP by helping to differentiate between benign and malignant lesions and aid in their classification[78,79]. AI based algorithms may also be useful in therapeutic ERCPs by increasing the probability of successful removal of biliary stones[75]. Further, data suggests that AI based interventions have the potential to reduce post-ERCP complications including acute pancreatitis[80].

Endoscopic ultrasound (EUS) has been introduced recently to aid in the diagnosis of pancreatobiliary diseases. However, the diagnostic accuracy of EUS also remains limited with most studies reporting the range to be 80%-95%[81]. AI may be instrumental in increasing the efficacy and accuracy of EUS in the diagnosis and prognostication of GI diseases[82].

**GASTROINTESTINAL SURGERY**

Patients frequently require ICU care in the peri-operative period of major GI surgeries for clinical stabilisation and optimisation of therapy. These patients require close monitoring for development of any post-operative complications which may affect their hospital course and increase morbidity or mortality. AI based tools may be instrumental in recognising patients at risk of developing post-operative complications who may benefit from intensive care and early intervention.

Acute appendicitis remains a common and dreaded abdominal emergency. However, its diagnosis is often missed, which may increase morbidity and mortality. ANN has shown promising results in diagnosis of acute appendicitis and has performed better than clinical scores like Alvarado clinical scoring system. This may aid in screening of patients presenting with acute abdomen and making an early diagnosis[83].

In patients undergoing liver transplantation, AI has been used to predict post-operative course, graft failure, recurrence of HCC and even survival after surgery[84-87]. ANN has also been used to predict in-hospital mortality in patients after primary liver cancer surgery[88].

Certain acute abdominal emergencies like abdominal aortic aneurysm (AAA) rupture may be associated with high mortality rates. Prompt recognition and early intervention may improve outcomes in such cases. CNN based model has been shown to have high accuracy of 99.1% with an AUROC of 0.99 for detecting AAA. Also, CNN based models may be effective in accurately detecting presence of any leak post AAA repair and predict in-hospital mortality in the post-operative period[89-91]. Further, AI using easily definable pre-operative parameters, has been shown to provide a simple and highly discriminant adjunct in accurately recognising patients at higher risk of death after AAA repair surgery[91].

Similarly, AI based algorithms have been used to predict clinical outcomes including post-operative complications and mortality in other major or emergency abdominal surgeries including bariatric and metabolic surgeries, duodenal switch surgeries, and even after inguinal hernia repair[92-95].

**NON-CLINICAL APPLICATIONS**

Apart from these clinical applications, AI may be helpful in several non-clinical applications in GI critical care. AI can help in assimilating and analysing huge databases, help in reducing human errors in data entry, and assist in conducting large scale multi-center trials[96].These intelligent database systems can also improve adherence to current clinical guidelines and protocols and aid in performing clinical audits and improve performance. Further, AI may also be instrumental in providing a more individualised patient care, and hence pave the way for precision medicine in the field of gastroenterology[97].

**LIMITATIONS TO AI APPLICATIONS**

The literature regarding use of AI in healthcare settings is increasing. However, most of the present studies have small sample sizes and are retrospective in nature. The literature on ICU patients is even more limited, restricting the use of AI in these patients. Moreover, comparison between different studies is difficult, as they have used different types of AI tools, with new tools being added frequently. Use of patient data for developing AI algorithms may lead to privacy and medico-legal issues which need to be adequately addressed by designing and implementing appropriate regulations and guidelines. Further, issues related to liability, reliability and safety of AI applications need to be addressed before widespread implementation and acceptance of AI in the current healthcare system becomes possible.

**FUTURE DIRECTIONS**

AI may form an important component of healthcare management and a lucrative adjunct to intensive care physicians in the future. However, large scale trials need to be conducted, especially in ICU patients, to evaluate and validate the efficacy and safety of AI. Further, standardisation of AI tools and algorithms must be done to ensure their comparability. For AI to be integrated in the routine clinical practice, healthcare workers need to be trained regarding safe and effective use of AI to ensure its proper utilisation and interpretation. Appropriate rules and regulations must be implemented to prevent any violation of patient privacy and maintain confidentiality of patient data.

**CONCLUSION**

With a huge increase in digitalisation of data and increased availability of big data, AI holds immense promise to change the landscape of healthcare in the not-so-distant future. It has the potential to improve diagnostics, predict progression and complications, and predict outcomes of critically ill gastroenterology patients thereby, reducing medical errors, increasing efficiency and improving clinical outcomes. AI can potentially reduce the number of invasive procedures and hence, reduce complication rates and provide a safer environment. However, there still remains issues regarding its safety, liability, legality, and patient privacy, which need to be addressed before it is incorporated in mainstream clinical care. Even though it may not be able to replace the physician’s clinical acumen, it can be a good supplement and may aid in improving patient care and safety.

**REFERENCES**

1 **Copeland BJ.** "Artificial Intelligence". Encyclopedia Britannica. Cited 1 October 2023. Available from: https://www.britannica.com/technology/artificial-intelligence

2 **Hanson CW 3rd**, Marshall BE. Artificial intelligence applications in the intensive care unit. *Crit Care Med* 2001; **29**: 427-435 [PMID: 11269246 DOI: 10.1097/00003246-200102000-00038]

3 **Pavlidis P**, Crichton S, Lemmich Smith J, Morrison D, Atkinson S, Wyncoll D, Ostermann M. Improved outcome of severe acute pancreatitis in the intensive care unit. *Crit Care Res Pract* 2013; **2013**: 897107 [PMID: 23662207 DOI: 10.1155/2013/897107]

4 **Banks PA**, Bollen TL, Dervenis C, Gooszen HG, Johnson CD, Sarr MG, Tsiotos GG, Vege SS; Acute Pancreatitis Classification Working Group. Classification of acute pancreatitis--2012: revision of the Atlanta classification and definitions by international consensus. *Gut* 2013; **62**: 102-111 [PMID: 23100216 DOI: 10.1136/gutjnl-2012-302779]

5 **Huang J**, Qu HP, Zheng YF, Song XW, Li L, Xu ZW, Mao EQ, Chen EZ. The revised Atlanta criteria 2012 altered the classification, severity assessment and management of acute pancreatitis. *Hepatobiliary Pancreat Dis Int* 2016; **15**: 310-315 [PMID: 27298108 DOI: 10.1016/s1499-3872(15)60040-6]

6 **Lin YP,** Lin CC. The Application of Artificial Intelligence Technology in the Diagnosis of Acute Pancreatitis, 2019 Prognostics and System Health Management Conference (PHM-Paris), Paris, France, 2019; 244-248 [DOI: 10.1109/PHM-Paris.2019.00048]

7 **Ikeda M**, Ito S, Ishigaki T, Yamauchi K. Evaluation of a neural network classifier for pancreatic masses based on CT findings. *Comput Med Imaging Graph* 1997; **21**: 175-183 [PMID: 9258595 DOI: 10.1016/s0895-6111(97)00006-2]

8 **Aranda-Narváez JM**, González-Sánchez AJ, Montiel-Casado MC, Titos-García A, Santoyo-Santoyo J. Acute necrotizing pancreatitis: Surgical indications and technical procedures. *World J Clin Cases* 2014; **2**: 840-845 [PMID: 25516858 DOI: 10.12998/wjcc.v2.i12.840]

9 **Jha AK**, Goenka MK, Kumar R, Suchismita A. Endotherapy for pancreatic necrosis: An update. *JGH Open* 2019; **3**: 80-88 [PMID: 30834345 DOI: 10.1002/jgh3.12109]

10 **Kiss S**, Pintér J, Molontay R, Nagy M, Farkas N, Sipos Z, Fehérvári P, Pecze L, Földi M, Vincze Á, Takács T, Czakó L, Izbéki F, Halász A, Boros E, Hamvas J, Varga M, Mickevicius A, Faluhelyi N, Farkas O, Váncsa S, Nagy R, Bunduc S, Hegyi PJ, Márta K, Borka K, Doros A, Hosszúfalusi N, Zubek L, Erőss B, Molnár Z, Párniczky A, Hegyi P, Szentesi A; Hungarian Pancreatic Study Group. Early prediction of acute necrotizing pancreatitis by artificial intelligence: a prospective cohort-analysis of 2387 cases. *Sci Rep* 2022; **12**: 7827 [PMID: 35552440 DOI: 10.1038/s41598-022-11517-w]

11 **Juneja D**, Gopal PB, Ravula M. Scoring systems in acute pancreatitis: which one to use in intensive care units? *J Crit Care* 2010; **25**: 358.e9-358.e15 [PMID: 20149591 DOI: 10.1016/j.jcrc.2009.12.010]

12 **Windsor JA**. Assessment of the severity of acute pancreatitis: no room for complacency. *Pancreatology* 2008; **8**: 105-109 [PMID: 18382096 DOI: 10.1159/000123604]

13 **Corfield AP**, Cooper MJ, Williamson RC, Mayer AD, McMahon MJ, Dickson AP, Shearer MG, Imrie CW. Prediction of severity in acute pancreatitis: prospective comparison of three prognostic indices. *Lancet* 1985; **2**: 403-407 [PMID: 2863441 DOI: 10.1016/s0140-6736(85)92733-3]

14 **Jin X**, Ding Z, Li T, Xiong J, Tian G, Liu J. Comparison of MPL-ANN and PLS-DA models for predicting the severity of patients with acute pancreatitis: An exploratory study. *Am J Emerg Med* 2021; **44**: 85-91 [PMID: 33582613 DOI: 10.1016/j.ajem.2021.01.044]

15 **Mofidi R**, Duff MD, Madhavan KK, Garden OJ, Parks RW. Identification of severe acute pancreatitis using an artificial neural network. *Surgery* 2007; **141**: 59-66 [PMID: 17188168 DOI: 10.1016/j.surg.2006.07.022]

16 **Halonen KI**, Leppäniemi AK, Lundin JE, Puolakkainen PA, Kemppainen EA, Haapiainen RK. Predicting fatal outcome in the early phase of severe acute pancreatitis by using novel prognostic models. *Pancreatology* 2003; **3**: 309-315 [PMID: 12890993 DOI: 10.1159/000071769]

17 **Andersson B**, Andersson R, Ohlsson M, Nilsson J. Prediction of severe acute pancreatitis at admission to hospital using artificial neural networks. *Pancreatology* 2011; **11**: 328-335 [PMID: 21757970 DOI: 10.1159/000327903]

18 **Johnson CD**, Abu-Hilal M. Persistent organ failure during the first week as a marker of fatal outcome in acute pancreatitis. *Gut* 2004; **53**: 1340-1344 [PMID: 15306596 DOI: 10.1136/gut.2004.039883]

19 **Petrov MS**, Shanbhag S, Chakraborty M, Phillips AR, Windsor JA. Organ failure and infection of pancreatic necrosis as determinants of mortality in patients with acute pancreatitis. *Gastroenterology* 2010; **139**: 813-820 [PMID: 20540942 DOI: 10.1053/j.gastro.2010.06.010]

20 **Hong WD**, Chen XR, Jin SQ, Huang QK, Zhu QH, Pan JY. Use of an artificial neural network to predict persistent organ failure in patients with acute pancreatitis. *Clinics (Sao Paulo)* 2013; **68**: 27-31 [PMID: 23420153 DOI: 10.6061/clinics/2013(01)rc01]

21 **Fei Y**, Gao K, Li WQ. Artificial neural network algorithm model as powerful tool to predict acute lung injury following to severe acute pancreatitis. *Pancreatology* 2018; **18**: 892-899 [PMID: 30268673 DOI: 10.1016/j.pan.2018.09.007]

22 **Fei Y**, Hu J, Gao K, Tu J, Li WQ, Wang W. Predicting risk for portal vein thrombosis in acute pancreatitis patients: A comparison of radical basis function artificial neural network and logistic regression models. *J Crit Care* 2017; **39**: 115-123 [PMID: 28246056 DOI: 10.1016/j.jcrc.2017.02.032]

23 **Fei Y**, Gao K, Hu J, Tu J, Li WQ, Wang W, Zong GQ. Predicting the incidence of portosplenomesenteric vein thrombosis in patients with acute pancreatitis using classification and regression tree algorithm. *J Crit Care* 2017; **39**: 124-130 [PMID: 28254727 DOI: 10.1016/j.jcrc.2017.02.019]

24 **Lin F**, Lu R, Han D, Fan Y, Zhang Y, Pan P. A prediction model for acute respiratory distress syndrome among patients with severe acute pancreatitis: a retrospective analysis. *Ther Adv Respir Dis* 2022; **16**: 17534666221122592 [PMID: 36065909 DOI: 10.1177/17534666221122592]

25 **Zhang W**, Chang Y, Ding Y, Zhu Y, Zhao Y, Shi R. To Establish an Early Prediction Model for Acute Respiratory Distress Syndrome in Severe Acute Pancreatitis Using Machine Learning Algorithm. *J Clin Med* 2023; **12** [PMID: 36902504 DOI: 10.3390/jcm12051718]

26 **Yasuda H**, Horibe M, Sanui M, Sasaki M, Suzuki N, Sawano H, Goto T, Ikeura T, Takeda T, Oda T, Ogura Y, Miyazaki D, Kitamura K, Chiba N, Ozaki T, Yamashita T, Koinuma T, Oshima T, Yamamoto T, Hirota M, Sato M, Miyamoto K, Mine T, Misumi T, Takeda Y, Iwasaki E, Kanai T, Mayumi T. Etiology and mortality in severe acute pancreatitis: A multicenter study in Japan. *Pancreatology* 2020; **20**: 307-317 [PMID: 32198057 DOI: 10.1016/j.pan.2020.03.001]

27 **Bugiantella W**, Rondelli F, Boni M, Stella P, Polistena A, Sanguinetti A, Avenia N. Necrotizing pancreatitis: A review of the interventions. *Int J Surg* 2016; **28 Suppl 1**: S163-S171 [PMID: 26708848 DOI: 10.1016/j.ijsu.2015.12.038]

28 **Colvin SD**, Smith EN, Morgan DE, Porter KK. Acute pancreatitis: an update on the revised Atlanta classification. *Abdom Radiol (NY)* 2020; **45**: 1222-1231 [PMID: 31494708 DOI: 10.1007/s00261-019-02214-w]

29 **Petrov MS**, Pylypchuk RD, Uchugina AF. A systematic review on the timing of artificial nutrition in acute pancreatitis. *Br J Nutr* 2009; **101**: 787-793 [PMID: 19017421 DOI: 10.1017/S0007114508123443]

30 **Keogan MT**, Lo JY, Freed KS, Raptopoulos V, Blake S, Kamel IR, Weisinger K, Rosen MP, Nelson RC. Outcome analysis of patients with acute pancreatitis by using an artificial neural network. *Acad Radiol* 2002; **9**: 410-419 [PMID: 11942655 DOI: 10.1016/s1076-6332(03)80186-1]

31 **Ding N**, Guo C, Li C, Zhou Y, Chai X. An Artificial Neural Networks Model for Early Predicting In-Hospital Mortality in Acute Pancreatitis in MIMIC-III. *Biomed Res Int* 2021; **2021**: 6638919 [PMID: 33575333 DOI: 10.1155/2021/6638919]

32 **Wu S**, Zhou Q, Cai Y, Duan X. Development and validation of a prediction model for the early occurrence of acute kidney injury in patients with acute pancreatitis. *Ren Fail* 2023; **45**: 2194436 [PMID: 36999227 DOI: 10.1080/0886022X.2023.2194436]

33 **Mathiesen UL**, Franzén LE, Aselius H, Resjö M, Jacobsson L, Foberg U, Frydén A, Bodemar G. Increased liver echogenicity at ultrasound examination reflects degree of steatosis but not of fibrosis in asymptomatic patients with mild/moderate abnormalities of liver transaminases. *Dig Liver Dis* 2002; **34**: 516-522 [PMID: 12236486 DOI: 10.1016/s1590-8658(02)80111-6]

34 **Byra M**, Styczynski G, Szmigielski C, Kalinowski P, Michałowski Ł, Paluszkiewicz R, Ziarkiewicz-Wróblewska B, Zieniewicz K, Sobieraj P, Nowicki A. Transfer learning with deep convolutional neural network for liver steatosis assessment in ultrasound images. *Int J Comput Assist Radiol Surg* 2018; **13**: 1895-1903 [PMID: 30094778 DOI: 10.1007/s11548-018-1843-2]

35 **Biswas M**, Kuppili V, Edla DR, Suri HS, Saba L, Marinhoe RT, Sanches JM, Suri JS. Symtosis: A liver ultrasound tissue characterization and risk stratification in optimized deep learning paradigm. *Comput Methods Programs Biomed* 2018; **155**: 165-177 [PMID: 29512496 DOI: 10.1016/j.cmpb.2017.12.016]

36 **Hashem S**, Esmat G, Elakel W, Habashy S, Raouf SA, Elhefnawi M, Eladawy M, ElHefnawi M. Comparison of Machine Learning Approaches for Prediction of Advanced Liver Fibrosis in Chronic Hepatitis C Patients. *IEEE/ACM Trans Comput Biol Bioinform* 2018; **15**: 861-868 [PMID: 28391204 DOI: 10.1109/TCBB.2017.2690848]

37 **Kataria S,** Juneja D, Singh O. Transient elastography (FibroScan) in critical care: Applications and limitations. *World J Meta-Anal* 2023; **11:** 340-350 [DOI: 0.13105/wjma.v11.i7.340]

38 **Gatos I**, Tsantis S, Spiliopoulos S, Karnabatidis D, Theotokas I, Zoumpoulis P, Loupas T, Hazle JD, Kagadis GC. Temporal stability assessment in shear wave elasticity images validated by deep learning neural network for chronic liver disease fibrosis stage assessment. *Med Phys* 2019; **46**: 2298-2309 [PMID: 30929260 DOI: 10.1002/mp.13521]

39 **Li W**, Huang Y, Zhuang BW, Liu GJ, Hu HT, Li X, Liang JY, Wang Z, Huang XW, Zhang CQ, Ruan SM, Xie XY, Kuang M, Lu MD, Chen LD, Wang W. Multiparametric ultrasomics of significant liver fibrosis: A machine learning-based analysis. *Eur Radiol* 2019; **29**: 1496-1506 [PMID: 30178143 DOI: 10.1007/s00330-018-5680-z]

40 **Piscaglia F**, Cucchetti A, Benlloch S, Vivarelli M, Berenguer J, Bolondi L, Pinna AD, Berenguer M. Prediction of significant fibrosis in hepatitis C virus infected liver transplant recipients by artificial neural network analysis of clinical factors. *Eur J Gastroenterol Hepatol* 2006; **18**: 1255-1261 [PMID: 17099373 DOI: 10.1097/01.meg.0000243885.55562.7e]

41 **Park HJ**, Lee SS, Park B, Yun J, Sung YS, Shim WH, Shin YM, Kim SY, Lee SJ, Lee MG. Radiomics Analysis of Gadoxetic Acid-enhanced MRI for Staging Liver Fibrosis. *Radiology* 2019; **290**: 380-387 [PMID: 30615554 DOI: 10.1148/radiol.2018181197]

42 **Magaz M**, Baiges A, Hernández-Gea V. Precision medicine in variceal bleeding: Are we there yet? *J Hepatol* 2020; **72**: 774-784 [PMID: 31981725 DOI: 10.1016/j.jhep.2020.01.008]

43 **Hong WD**, Ji YF, Wang D, Chen TZ, Zhu QH. Use of artificial neural network to predict esophageal varices in patients with HBV related cirrhosis. *Hepat Mon* 2011; **11**: 544-547 [PMID: 22087192]

44 **Dong TS**, Kalani A, Aby ES, Le L, Luu K, Hauer M, Kamath R, Lindor KD, Tabibian JH. Machine Learning-based Development and Validation of a Scoring System for Screening High-Risk Esophageal Varices. *Clin Gastroenterol Hepatol* 2019; **17**: 1894-1901.e1 [PMID: 30708109 DOI: 10.1016/j.cgh.2019.01.025]

45 **Yuan Q,** Zhao WL, Qin B. Big data and variceal rebleeding prediction in cirrhosis patients. *Artif Intell Gastroenterol* 2023; **4:** 1-9 [DOI: 10.35712/aig.v4.i1.1]

46 **Juneja D**, Gopal PB, Kapoor D, Raya R, Sathyanarayanan M, Malhotra P. Outcome of patients with liver cirrhosis admitted to a specialty liver intensive care unit in India. *J Crit Care* 2009; **24**: 387-393 [PMID: 19327335 DOI: 10.1016/j.jcrc.2008.12.013]

47 **Konerman MA**, Zhang Y, Zhu J, Higgins PD, Lok AS, Waljee AK. Improvement of predictive models of risk of disease progression in chronic hepatitis C by incorporating longitudinal data. *Hepatology* 2015; **61**: 1832-1841 [PMID: 25684666 DOI: 10.1002/hep.27750]

48 **Konerman MA**, Lu D, Zhang Y, Thomson M, Zhu J, Verma A, Liu B, Talaat N, Balis U, Higgins PDR, Lok ASF, Waljee AK. Assessing risk of fibrosis progression and liver-related clinical outcomes among patients with both early stage and advanced chronic hepatitis C. *PLoS One* 2017; **12**: e0187344 [PMID: 29108017 DOI: 10.1371/journal.pone.0187344]

49 **Banerjee R**, Das A, Ghoshal UC, Sinha M. Predicting mortality in patients with cirrhosis of liver with application of neural network technology. *J Gastroenterol Hepatol* 2003; **18**: 1054-1060 [PMID: 12911662 DOI: 10.1046/j.1440-1746.2003.03123.x]

50 **Lee HW**, Sung JJY, Ahn SH. Artificial intelligence in liver disease. *J Gastroenterol Hepatol* 2021; **36**: 539-542 [PMID: 33709605 DOI: 10.1111/jgh.15409]

51 **Sato M**, Morimoto K, Kajihara S, Tateishi R, Shiina S, Koike K, Yatomi Y. Machine-learning Approach for the Development of a Novel Predictive Model for the Diagnosis of Hepatocellular Carcinoma. *Sci Rep* 2019; **9**: 7704 [PMID: 31147560 DOI: 10.1038/s41598-019-44022-8]

52 **Singal AG**, Mukherjee A, Elmunzer BJ, Higgins PD, Lok AS, Zhu J, Marrero JA, Waljee AK. Machine learning algorithms outperform conventional regression models in predicting development of hepatocellular carcinoma. *Am J Gastroenterol* 2013; **108**: 1723-1730 [PMID: 24169273 DOI: 10.1038/ajg.2013.332]

53 **Hassan TM,** Elmogy M, Sallam E-S. Diagnosis of focal liver diseases based on deep learning technique for ultrasound images. *Arab J Sci Eng* 2017; **42:** 3127–3140 [DOI: 10.1007/s13369-016-2387-9]

54 **Wu K,** Chen X, Ding M. Deep learning based classification of focal liver lesions with contrast-enhanced ultrasound. *Optik* 2014; **125:** 4057–4063 [DOI: 10.1016/j.ijleo.2014.01.114]

55 **Yasaka K**, Akai H, Abe O, Kiryu S. Deep Learning with Convolutional Neural Network for Differentiation of Liver Masses at Dynamic Contrast-enhanced CT: A Preliminary Study. *Radiology* 2018; **286**: 887-896 [PMID: 29059036 DOI: 10.1148/radiol.2017170706]

56 **Zhen SH**, Cheng M, Tao YB, Wang YF, Juengpanich S, Jiang ZY, Jiang YK, Yan YY, Lu W, Lue JM, Qian JH, Wu ZY, Sun JH, Lin H, Cai XJ. Deep Learning for Accurate Diagnosis of Liver Tumor Based on Magnetic Resonance Imaging and Clinical Data. *Front Oncol* 2020; **10**: 680 [PMID: 32547939 DOI: 10.3389/fonc.2020.00680]

57 **Takayama T**, Ebinuma H, Tada S, Yamagishi Y, Wakabayashi K, Ojiro K, Kanai T, Saito H, Hibi T; Keio Association for the Study of Liver Diseases. Prediction of effect of pegylated interferon alpha-2b plus ribavirin combination therapy in patients with chronic hepatitis C infection. *PLoS One* 2011; **6**: e27223 [PMID: 22164207 DOI: 10.1371/journal.pone.0027223]

58 **Khosravi B**, Pourahmad S, Bahreini A, Nikeghbalian S, Mehrdad G. Five Years Survival of Patients After Liver Transplantation and Its Effective Factors by Neural Network and Cox Poroportional Hazard Regression Models. *Hepat Mon* 2015; **15**: e25164 [PMID: 26500682 DOI: 10.5812/hepatmon.25164]

59 **Rehman A**, Iscimen R, Yilmaz M, Khan H, Belsher J, Gomez JF, Hanson AC, Afessa B, Baron TH Sr, Gajic O. Prophylactic endotracheal intubation in critically ill patients undergoing endoscopy for upper GI hemorrhage. *Gastrointest Endosc* 2009; **69**: e55-e59 [PMID: 19481643 DOI: 10.1016/j.gie.2009.03.002]

60 **Pace F**, Buscema M, Dominici P, Intraligi M, Baldi F, Cestari R, Passaretti S, Bianchi Porro G, Grossi E. Artificial neural networks are able to recognize gastro-oesophageal reflux disease patients solely on the basis of clinical data. *Eur J Gastroenterol Hepatol* 2005; **17**: 605-610 [PMID: 15879721 DOI: 10.1097/00042737-200506000-00003]

61 **Shichijo S**, Nomura S, Aoyama K, Nishikawa Y, Miura M, Shinagawa T, Takiyama H, Tanimoto T, Ishihara S, Matsuo K, Tada T. Application of Convolutional Neural Networks in the Diagnosis of Helicobacter pylori Infection Based on Endoscopic Images. *EBioMedicine* 2017; **25**: 106-111 [PMID: 29056541 DOI: 10.1016/j.ebiom.2017.10.014]

62 **Mohan BP**, Khan SR, Kassab LL, Ponnada S, Mohy-Ud-Din N, Chandan S, Dulai PS, Kochhar GS. Convolutional neural networks in the computer-aided diagnosis of Helicobacter pylori infection and non-causal comparison to physician endoscopists: a systematic review with meta-analysis. *Ann Gastroenterol* 2021; **34**: 20-25 [PMID: 33414617 DOI: 10.20524/aog.2020.0542]

63 **de Groof AJ**, Struyvenberg MR, van der Putten J, van der Sommen F, Fockens KN, Curvers WL, Zinger S, Pouw RE, Coron E, Baldaque-Silva F, Pech O, Weusten B, Meining A, Neuhaus H, Bisschops R, Dent J, Schoon EJ, de With PH, Bergman JJ. Deep-Learning System Detects Neoplasia in Patients With Barrett's Esophagus With Higher Accuracy Than Endoscopists in a Multistep Training and Validation Study With Benchmarking. *Gastroenterology* 2020; **158**: 915-929.e4 [PMID: 31759929 DOI: 10.1053/j.gastro.2019.11.030]

64 **van der Sommen F**, Zinger S, Curvers WL, Bisschops R, Pech O, Weusten BL, Bergman JJ, de With PH, Schoon EJ. Computer-aided detection of early neoplastic lesions in Barrett's esophagus. *Endoscopy* 2016; **48**: 617-624 [PMID: 27100718 DOI: 10.1055/s-0042-105284]

65 **Das A**, Ben-Menachem T, Cooper GS, Chak A, Sivak MV Jr, Gonet JA, Wong RC. Prediction of outcome in acute lower-gastrointestinal haemorrhage based on an artificial neural network: internal and external validation of a predictive model. *Lancet* 2003; **362**: 1261-1266 [PMID: 14575969 DOI: 10.1016/S0140-6736(03)14568-0]

66 **Das A**, Ben-Menachem T, Farooq FT, Cooper GS, Chak A, Sivak MV Jr, Wong RC. Artificial neural network as a predictive instrument in patients with acute nonvariceal upper gastrointestinal hemorrhage. *Gastroenterology* 2008; **134**: 65-74 [PMID: 18061180 DOI: 10.1053/j.gastro.2007.10.037]

67 **Ayaru L**, Ypsilantis PP, Nanapragasam A, Choi RC, Thillanathan A, Min-Ho L, Montana G. Prediction of Outcome in Acute Lower Gastrointestinal Bleeding Using Gradient Boosting. *PLoS One* 2015; **10**: e0132485 [PMID: 26172121 DOI: 10.1371/journal.pone.0132485]

68 **Sengupta N**, Tapper EB. Derivation and Internal Validation of a Clinical Prediction Tool for 30-Day Mortality in Lower Gastrointestinal Bleeding. *Am J Med* 2017; **130**: 601.e1-601.e8 [PMID: 28065767 DOI: 10.1016/j.amjmed.2016.12.009]

69 **Wong GL**, Ma AJ, Deng H, Ching JY, Wong VW, Tse YK, Yip TC, Lau LH, Liu HH, Leung CM, Tsang SW, Chan CW, Lau JY, Yuen PC, Chan FK. Machine learning model to predict recurrent ulcer bleeding in patients with history of idiopathic gastroduodenal ulcer bleeding. *Aliment Pharmacol Ther* 2019; **49**: 912-918 [PMID: 30761584 DOI: 10.1111/apt.15145]

70 **Li B**, Meng MQ. Computer-based detection of bleeding and ulcer in wireless capsule endoscopy images by chromaticity moments. *Comput Biol Med* 2009; **39**: 141-147 [PMID: 19147126 DOI: 10.1016/j.compbiomed.2008.11.007]

71 **Pan G**, Yan G, Qiu X, Cui J. Bleeding detection in Wireless Capsule Endoscopy based on Probabilistic Neural Network. *J Med Syst* 2011; **35**: 1477-1484 [PMID: 20703770 DOI: 10.1007/s10916-009-9424-0]

72 **Hassan AR**, Haque MA. Computer-aided gastrointestinal hemorrhage detection in wireless capsule endoscopy videos. *Comput Methods Programs Biomed* 2015; **122**: 341-353 [PMID: 26390947 DOI: 10.1016/j.cmpb.2015.09.005]

73 **Xiao Jia**, Meng MQ. A deep convolutional neural network for bleeding detection in Wireless Capsule Endoscopy images. *Annu Int Conf IEEE Eng Med Biol Soc* 2016; **2016**: 639-642 [PMID: 28268409 DOI: 10.1109/EMBC.2016.7590783]

74 **Jovanovic P**, Salkic NN, Zerem E. Artificial neural network predicts the need for therapeutic ERCP in patients with suspected choledocholithiasis. *Gastrointest Endosc* 2014; **80**: 260-268 [PMID: 24593947 DOI: 10.1016/j.gie.2014.01.023]

75 **Huang L**, Xu Y, Chen J, Liu F, Wu D, Zhou W, Wu L, Pang T, Huang X, Zhang K, Yu H. An artificial intelligence difficulty scoring system for stone removal during ERCP: a prospective validation. *Endoscopy* 2023; **55**: 4-11 [PMID: 35554877 DOI: 10.1055/a-1850-6717]

76 **Kim T**, Kim J, Choi HS, Kim ES, Keum B, Jeen YT, Lee HS, Chun HJ, Han SY, Kim DU, Kwon S, Choo J, Lee JM. Artificial intelligence-assisted analysis of endoscopic retrograde cholangiopancreatography image for identifying ampulla and difficulty of selective cannulation. *Sci Rep* 2021; **11**: 8381 [PMID: 33863970 DOI: 10.1038/s41598-021-87737-3]

77 **Sugimoto Y**, Kurita Y, Kuwahara T, Satou M, Meguro K, Hosono K, Kubota K, Hara K, Nakajima A. Diagnosing malignant distal bile duct obstruction using artificial intelligence based on clinical biomarkers. *Sci Rep* 2023; **13**: 3262 [PMID: 36828831 DOI: 10.1038/s41598-023-28058-5]

78 **Jang SI**, Kim YJ, Kim EJ, Kang H, Shon SJ, Seol YJ, Lee DK, Kim KG, Cho JH. Diagnostic performance of endoscopic ultrasound-artificial intelligence using deep learning analysis of gallbladder polypoid lesions. *J Gastroenterol Hepatol* 2021; **36**: 3548-3555 [PMID: 34431545 DOI: 10.1111/jgh.15673]

79 **Marya NB**, Powers PD, Petersen BT, Law R, Storm A, Abusaleh RR, Rau P, Stead C, Levy MJ, Martin J, Vargas EJ, Abu Dayyeh BK, Chandrasekhara V. Identification of patients with malignant biliary strictures using a cholangioscopy-based deep learning artificial intelligence (with video). *Gastrointest Endosc* 2023; **97**: 268-278.e1 [PMID: 36007584 DOI: 10.1016/j.gie.2022.08.021]

80 **Cotton PB**, Lehman G, Vennes J, Geenen JE, Russell RC, Meyers WC, Liguory C, Nickl N. Endoscopic sphincterotomy complications and their management: an attempt at consensus. *Gastrointest Endosc* 1991; **37**: 383-393 [PMID: 2070995 DOI: 10.1016/s0016-5107(91)70740-2]

81 **Kuwahara T**, Hara K, Mizuno N, Haba S, Okuno N, Kuraishi Y, Fumihara D, Yanaidani T, Ishikawa S, Yasuda T, Yamada M, Onishi S, Yamada K, Tanaka T, Tajika M, Niwa Y, Yamaguchi R, Shimizu Y. Artificial intelligence using deep learning analysis of endoscopic ultrasonography images for the differential diagnosis of pancreatic masses. *Endoscopy* 2023; **55**: 140-149 [PMID: 35688454 DOI: 10.1055/a-1873-7920]

82 **Huang J**, Fan X, Liu W. Applications and Prospects of Artificial Intelligence-Assisted Endoscopic Ultrasound in Digestive System Diseases. *Diagnostics (Basel)* 2023; **13** [PMID: 37685350 DOI: 10.3390/diagnostics13172815]

83 **Park SY**, Kim SM. Acute appendicitis diagnosis using artificial neural networks. *Technol Health Care* 2015; **23 Suppl 2**: S559-S565 [PMID: 26410524 DOI: 10.3233/THC-150994]

84 **Qiao G**, Li J, Huang A, Yan Z, Lau WY, Shen F. Artificial neural networking model for the prediction of post-hepatectomy survival of patients with early hepatocellular carcinoma. *J Gastroenterol Hepatol* 2014; **29**: 2014-2020 [PMID: 24989634 DOI: 10.1111/jgh.12672]

85 **Yamashita R**, Long J, Saleem A, Rubin DL, Shen J. Deep learning predicts postsurgical recurrence of hepatocellular carcinoma from digital histopathologic images. *Sci Rep* 2021; **11**: 2047 [PMID: 33479370 DOI: 10.1038/s41598-021-81506-y]

86 **Rodriguez-Luna H**, Vargas HE, Byrne T, Rakela J. Artificial neural network and tissue genotyping of hepatocellular carcinoma in liver-transplant recipients: prediction of recurrence. *Transplantation* 2005; **79**: 1737-1740 [PMID: 15973178 DOI: 10.1097/01.tp.0000161794.32007.d1]

87 **Lau L**, Kankanige Y, Rubinstein B, Jones R, Christophi C, Muralidharan V, Bailey J. Machine-Learning Algorithms Predict Graft Failure After Liver Transplantation. *Transplantation* 2017; **101**: e125-e132 [PMID: 27941428 DOI: 10.1097/TP.0000000000001600]

88 **Shi HY**, Lee KT, Lee HH, Ho WH, Sun DP, Wang JJ, Chiu CC. Comparison of artificial neural network and logistic regression models for predicting in-hospital mortality after primary liver cancer surgery. *PLoS One* 2012; **7**: e35781 [PMID: 22563399 DOI: 10.1371/journal.pone.0035781]

89 **Camara JR**, Tomihama RT, Pop A, Shedd MP, Dobrowski BS, Knox CJ, Abou-Zamzam AM Jr, Kiang SC. Development of a convolutional neural network to detect abdominal aortic aneurysms. *J Vasc Surg Cases Innov Tech* 2022; **8**: 305-311 [PMID: 35692515 DOI: 10.1016/j.jvscit.2022.04.003]

90 **Hahn S**, Perry M, Morris CS, Wshah S, Bertges DJ. Machine deep learning accurately detects endoleak after endovascular abdominal aortic aneurysm repair. *JVS Vasc Sci* 2020; **1**: 5-12 [PMID: 34617036 DOI: 10.1016/j.jvssci.2019.12.003]

91 **Wise ES**, Hocking KM, Brophy CM. Prediction of in-hospital mortality after ruptured abdominal aortic aneurysm repair using an artificial neural network. *J Vasc Surg* 2015; **62**: 8-15 [PMID: 25953014 DOI: 10.1016/j.jvs.2015.02.038]

92 **Wise E**, Leslie D, Amateau S, Hocking K, Scott A, Dutta N, Ikramuddin S. Prediction of thirty-day morbidity and mortality after duodenal switch using an artificial neural network. *Surg Endosc* 2023; **37**: 1440-1448 [PMID: 35764835 DOI: 10.1007/s00464-022-09378-5]

93 **Wise ES**, Hocking KM, Kavic SM. Prediction of excess weight loss after laparoscopic Roux-en-Y gastric bypass: data from an artificial neural network. *Surg Endosc* 2016; **30**: 480-488 [PMID: 26017908 DOI: 10.1007/s00464-015-4225-7]

94 **Gao J**, Zagadailov P, Merchant AM. The Use of Artificial Neural Network to Predict Surgical Outcomes After Inguinal Hernia Repair. *J Surg Res* 2021; **259**: 372-378 [PMID: 33097206 DOI: 10.1016/j.jss.2020.09.021]

95 **Xue Q**, Wen D, Ji MH, Tong J, Yang JJ, Zhou CM. Developing Machine Learning Algorithms to Predict Pulmonary Complications After Emergency Gastrointestinal Surgery. *Front Med (Lausanne)* 2021; **8**: 655686 [PMID: 34409047 DOI: 10.3389/fmed.2021.655686]

96 **van den Heever M**, Mittal A, Haydock M, Windsor J. The use of intelligent database systems in acute pancreatitis--a systematic review. *Pancreatology* 2014; **14**: 9-16 [PMID: 24555973 DOI: 10.1016/j.pan.2013.11.010]

97 **Su TH**, Wu CH, Kao JH. Artificial intelligence in precision medicine in hepatology. *J Gastroenterol Hepatol* 2021; **36**: 569-580 [PMID: 33709606 DOI: 10.1111/jgh.15415]

**Footnotes**

**Conflict-of-interest statement:** All the author declare that they have no conflict of interest.

**Open-Access:** This article is an open-access article that was selected by an in-house editor and fully peer-reviewed by external reviewers. It is distributed in accordance with the Creative Commons Attribution NonCommercial (CC BY-NC 4.0) license, which permits others to distribute, remix, adapt, build upon this work non-commercially, and license their derivative works on different terms, provided the original work is properly cited and the use is non-commercial. See: https://creativecommons.org/Licenses/by-nc/4.0/

**Provenance and peer review:** Invited article; Externally peer reviewed.

**Peer-review model:** Single blind

**Peer-review started:** October 21, 2023

**First decision:** December 7, 2023

**Article in press:**

**Specialty type:** Critical care medicine

**Country/Territory of origin:** India

**Peer-review report’s scientific quality classification**

Grade A (Excellent): 0

Grade B (Very good): 0

Grade C (Good): C

Grade D (Fair): 0

Grade E (Poor): 0

**P-Reviewer:** Sun D, China **S-Editor:** Liu JH **L-Editor:** A **P-Editor:**

**Table 1 Potential clinical applications of artificial intelligence in critical care gastroenterology**

|  |  |  |
| --- | --- | --- |
| **Organ involved** | **Clinical condition** | **Clinical applications** |
| Pancreas | Acute pancreatitis | Prediction of severity; Prediction of local and systemic complications; Prediction of organ failure; Prediction of mortality |
| Liver | Chronic liver disease | Diagnosis; Staging of fibrosis; Prediction of complications; Predicting disease progression; Prognosis; Predicting need for liver transplantation |
| Liver lesions/tumours | Diagnosis and classification; Differentiating between benign and malignant lesions |
| Hepatocellular carcinoma | Diagnosis; Staging; Response to therapy |
| Intestine | Gastroesophageal reflux disease | Diagnosis |
| Helicobacter pylori infection | Diagnosis |
| Intestinal lesions | Diagnosis; Differentiating between benign and malignant lesions |
| Intestinal bleeding | Predicting risk of bleeding and re-bleeding; Diagnosis; Identifying source of bleeding |
| Gall bladder and bile duct | Gall stones | Diagnosis; Removal of stones; Predicting need and difficulty of ERCP |
| Bile duct obstruction | Diagnosis |
| Gastro-surgery | Appendicitis | Diagnosis |
| Liver transplantation | Predict post-operative course; Predict graft failure; Predict recurrence of HCC; Predict in-hospital mortality |
| Abdominal aortic aneurysm | Diagnosis; Prediction of post-operative complications; Prediction of post-operative mortality |

ERCP: Endoscopic retrograde cholangiopancreatography; HCC: Hepatocellular carcinoma.