ISSN 2616-5791 Vol.4, Issue 12: 27-34, DOI: 10.25236/AJMHS.2023.041204

Research progress of machine learning in the diagnosis and prediction of acute abdomen

Liu Zhichen[1,a], Luo Xu[2,b,*]

[1]School of Nursing, Zunyi Medical University, Zunyi, 563000, China
[2]School of Information Engineering, Zunyi Medical University, Zunyi, 563000, China
[a]1540636422@qq.com, [b]silyaseln@live.cn
[*]Corresponding author

Abstract: *Acute abdomen is one of the most common diseases in the emergency department, referring to a group of abdominal diseases that are characterized by acute onset, rapid onset, and frequent changes, with abdominal pain as the main symptom and require urgent treatment. Machine learning is a major research direction in artificial intelligence, with the ability to analyze a large amount of complex data and extract data patterns from a large amount of data, thereby forming rules for data classification and prediction. In recent years, with the informatization of patient record data, research on the combination of machine learning and medical treatment has been increasing. Some studies believe that machine learning algorithms have brought new possibilities for the diagnosis and prediction of acute abdomen. This article reviews the research progress of machine learning in the diagnosis and prediction of acute abdomen, including experimental data, feature selection, algorithm models, and performance evaluation indicators, A systematic summary of the research status of machine learning technology in the application of acute abdominal diseases was conducted. Firstly, with regard to machine learning algorithms, we explicate the utilization of such algorithms in the context of acute abdomen. Secondly, focusing on practical applications, this article elaborates on disease assisted diagnosis and disease prediction through specific experiments; Finally, the limitations of machine learning in the application of acute abdomen and propose prospects were pointed out.*

Keywords: *Acute Abdomen, Machine Learning, Artificial Intelligence, Computer-Assisted Diagnosis, Predictions*

1. Introduction

Acute abdomen refers to a condition characterized by sudden onset, rapid progression, and severe symptoms, including abdominal pain lasting for 7 days or less, which necessitates urgent intervention. Acute abdomen is a commonly encountered medical condition in the field of emergency medicine, accounting for approximately 5% to 10% of emergency department visits.[1-3],In the population aged over 65 years, this proportion even exceeds 20%[4, 5],Among pregnant women, the rate of acute abdomen complicating pregnancy accounted for 1.53% of hospitalized pregnant women during the same period [6],Pediatric acute abdomen is also one of the common pediatric emergencies [7].There is a limited number of systematic epidemiological surveys on acute abdomen in China. Combining with bulk case reports from certain institutions [8] , such diseases could constitute 1/5 to 1/4 of emergency visits, making it one of the most commonly encountered conditions for emergency physicians. Timely and accurate triage and management are imperative for acute abdomen, as an incorrect assessment would lead to delayed treatment or even jeopardize the patient's life[9, 10].

Acute abdomen encompasses a multidisciplinary field, including internal medicine, surgery, pediatrics, and obstetrics and gynecology. Due to varied etiologies, the location and nature of abdominal pain differ among patients. In clinical practice, healthcare professionals often rely on their own clinical experience to conduct initial assessments of patients with acute abdomen. However, deficiencies in experience among some healthcare professionals, atypical symptoms and signs of common diseases and non-specific symptoms and signs of rare diseases, can make it difficult to make accurate judgments, leading to misdiagnosis and missed diagnosis of acute abdomen[11-15].

In recent years, the rapid rise of artificial intelligence has been a hot topic in healthcare, and the application of AI in the diagnosis and prediction of acute abdomen has gained significant traction. Many scholars have engaged in researches in this field. This article aims to provide an overview of the

ISSN 2616-5791 Vol.4, Issue 12: 27-34, DOI: 10.25236/AJMHS.2023.041204

research progress regarding the application of machine learning in the diagnosis and prediction of acute abdomen.

2. Machine learning

Artificial intelligence (AI) is a branch of computer science. It is a technology that uses computers to replace human brains for cognitive, recognition, analysis, and decision-making functions. Its essence lies in simulating human consciousness and mental information processes, possessing multidisciplinary integration and highly complex characteristics. In recent years, AI has not only flourished in various fields such as technology and engineering but has also begun to make strides in the field of healthcare. AI in medicine can be divided into two major branches: virtual and physical[16].The virtual branch, represented by machine learning, is currently mainly applied in the medical field in two aspects: firstly, by learning from existing medical data to understand a patient's symptoms, clinical manifestations, and ancillary examination data, in order to analyze and assist in diagnosing and predicting diseases[17];secondly, by effectively combining image processing, computer vision, and medical image analysis, through system processing, to annotate abnormal signs, thereby helping medical personnel quickly detect lesions, reduce the time required for image review or endoscopic image reading, and improve diagnostic accuracy and efficiency in disease diagnosis[18].The application forms of the physical branch include tangible objects, medical equipment, and increasingly complex robots involved in providing care (care robots)[19].

The rapid development of AI in recent years is due to the enormous and continuously growing amount of data, the computing power of computers, and the emergence of improved machine learning algorithms. Machine learning is a subset of AI and a major technology for simulating the human brain. It plays a key role in the development of AI. Machine learning is essentially a multi-level representation learning, which refers to analyzing and learning large amounts of data, discovering the underlying structure within the data, and analyzing and mining data patterns. Based on these patterns, predictions and optimal decisions can be made for unknown data.

Machine learning can be divided into supervised learning and unsupervised learning [20].Supervised learning uses known samples with assigned categories to train and predict known targets or output results. The most representative tasks in supervised learning are classification and regression. Classification is a supervised learning method for modeling or predicting discrete random variables, wherein the ultimate outcome manifests as the categorical designation or discrete value label to which the feature value pertains. Regression is a supervised learning method for modeling or predicting continuous random variables, where the label of the feature vector is a continuous value. Unsupervised learning, on the other hand, involves finding the inherent correlations and patterns within unlabeled data and uncovering hidden data structures. The representative task of unsupervised learning is clustering, which categorizes similar objects into different groups or subsets based on clustering methods, so that members in the same group or subset have similar attributes. In the medical field, where labeling data is costly, there may be a stronger demand for semi-supervised learning, where only a portion of the data is labeled, enabling the learner to improve its performance using unlabeled data without relying on external interactions[21].

3. Research on machine learning in acute abdomen

3.1 Diagnostic identification

In order to improve the accuracy of diagnosing acute abdominal conditions and reduce misdiagnosis and missed diagnosis rates, many scholars have conducted research on the application of machine learning in assisting the diagnosis of acute abdominal conditions.

3.1.1 Auxiliary diagnosis of acute abdomen

As early as 1972, Shepherd et al [22] utilized the Bayesian algorithm to construct a computer-aided diagnosis system and conducted a prospective experimental study on 304 patients with acute abdominal pain. They compared the diagnosis of clinical physicians and computer-aided diagnosis in accuracy, reliability, and determinism. The error rate of clinical physicians was 20.4%, while the error rate of the computer-aided system was 8.2%. The results indicated that the computer-aided diagnosis system could be used to assist clinical physicians in the diagnosis of patients with acute abdominal pain. Khumrin et al[23] trained a machine learning model on 208 clinical cases of abdominal pain, involving Bayesian, Support Vector Machine, Neural Network, Decision Tree, and Logitboost methods. The model was used to predict the diagnosis of five diseases and achieved an accuracy rate of 91.8%. McAdam et al[24] conducted a 12-year study involving 5512 patients with acute abdominal pain. During the 12 years, a computer-aided diagnosis system was used for diagnosis, which increased the diagnostic accuracy of primary doctors in the hospital from 45%-55% to 70%-80% and reduced the perforation rate of appendicitis cases from 27% to 12.5%. Dombal et al [25] designed a computer-aided diagnosis system to diagnose whether patients with unexplained acute abdominal pain had cancer. Finally, a study was conducted on 138 cases, achieving an accuracy rate of 84.7%. Kurzyński et al [26] used a Bayesian-based machine learning method to diagnose patients with acute abdominal pain and identified 19 diagnostic categories among 1196 patients. The research concluded that clinical physicians with computer-aided diagnosis had an approximately 20% higher diagnostic accuracy than those without computer-aided diagnosis. Papadopoulos et al[27] applied machine learning methods such as neural network classifiers, Bayesian algorithms, and decision trees to the diagnosis of acute abdominal pain and 4387 cases were included in the training data set. The accuracy of the methods was tested on 2000 additional cases, and the study demonstrated that neural network classifiers had the highest classification decision effect with an accuracy rate of 75.74%.

Scholars have frequently conducted research on the computer-aided diagnosis of patients with acute abdominal pain using machine learning, including studies on the auxiliary diagnosis of women and children with acute abdominal pain. Acute abdominal pain in gynecology often occurs in the lower abdomen, which is easily confused with digestive system diseases such as acute appendicitis. The misdiagnosis rate of ectopic pregnancy can be as high as 5%-10% [28],Walmsley et al [29] constructed a joint diagnosis system based on Bayesian machine learning and conducted a prospective investigation on 393 women with abdominal pain lasting less than one week. The results showed that the computer's diagnostic predictions matched the final diagnosis of 81.6% of the patients. Due to the weak language expression ability of children and their lack of cooperation with physical examinations, the diagnosis of pediatric abdominal pain becomes more difficult. Wilk et al [30] used rough set theory to perform feature learning on 627 pediatric patients who visited the emergency department with abdominal pain and extracted 12 most relevant features to generate decision rules, which helped emergency medical personnel to make preliminary assessments of children with abdominal pain.

3.1.2 Quick identification of specific acute abdomen

In recent years, there has been an increasing amount of researches using machine learning algorithms to assist in the diagnosis of specific acute abdominal conditions. And the diagnostic models constructed have shown a good level of accuracy. In this part, the utilization of machine learning in the diagnoses of celiac disease, acute appendicitis, pancreas, cholelithiasis and cholecystitis are taken as examples.

Celiac disease presents a challenge in diagnosis due to its various clinical manifestations and symptoms similar to other diseases. Small intestinal biopsy is the gold standard for diagnosing celiac disease. In order to develop a simple, reliable, and effective clinical decision-making tool, Tenório et al[[31]constructed five machine learning models, including decision trees, Bayesian inference, k-nearest neighbors algorithm, support vector machines, and artificial neural networks, to rapidly identify cases of celiac disease. Ultimately, the Bayesian classifier demonstrated the highest accuracy, with an accuracy rate of 80.0%, sensitivity of 0.78, specificity of 0.80, and AUC (area under the curve) of 0.84. These results indicate that the constructed machine learning models have excellent accuracy in identifying cases of celiac disease and can be used as aid tools.

For patients with acute appendicitis, especially children under the age of 6, differentiating their symptoms and signs from those of gastroenteritis is challenging. Reismann et al[32] developed a supervised machine learning algorithm to establish a decision model for suspected acute appendicitis in children. This model utilized data including complete blood cell count, C-reactive protein (CRP) levels, and ultrasound examination of appendix diameter to diagnose appendicitis and identify complicated appendicitis. The diagnostic accuracy of the model was 97%, with a specificity of 67% and sensitivity of 93%. The accuracy of identifying complicated appendicitis was 51%, with a specificity of 33% and sensitivity of 95%. Park et al[33] constructed an appendicitis diagnostic algorithm based on a three-dimensional convolutional neural network. By training the network using CT image data of patients with and without appendicitis, they were able to quickly identify appendicitis among patients with acute abdominal pain. The accuracy of the acute appendicitis classification algorithm was 91.5%, with a sensitivity of 90.2% and specificity of 92.0%.

The diagnosis of this condition presents a daunting challenge due to the non-specificity of

ISSN 2616-5791 Vol.4, Issue 12: 27-34, DOI: 10.25236/AJMHS.2023.041204

symptoms such as abdominal pain and elevated enzyme levels, as well as the normal appearance of the pancreas on CT scans after resolution of acute pancreatitis.Mashayekhi et al[34] constructed a diagnostic model for pancreatitis using support vector machines, which differentiated between functional abdominal pain, recurrent pancreatitis, and chronic pancreatitis based on quantitative radiological features of the pancreatic on CT scans. The results demonstrated good classification accuracy of machine learning, with an overall accuracy rate of 82.1%. Surgery is the primary treatment modality for patients with pancreatic tumors. Accurate diagnosis and timely surgery are crucial to their successful treatment. Si et al[35] developed a FEE-DL model based on deep learning for the diagnosis of pancreatic tumors. The model was trained on 143,945 clinical CT images from 319 patients and tested on an independent test dataset of 107,036 clinical CT images from 347 patients, achieving an accuracy rate of 82.7%, an AUC of 0.871, and an F1 score of 88.5%. Furthermore, the average examination time per patient was reduced from a minimum of 8 minutes with manual inspection to 18.6 seconds. These results demonstrate that the model can provide efficient and accurate preoperative diagnosis, aiding in the surgical treatment of pancreatic tumors. The diagnosis of autoimmune pancreatitis (AIP) is challenging due to the similarities in ultrasound and cross-sectional imaging findings between AIP and pancreatic ductal adenocarcinoma (PDAC), as well as the suboptimal tissue sampling techniques for AIP. Marya et al[36] developed a convolutional neural network (CNN) model based on endoscopic ultrasound (EUS) to differentiate AIP from PDAC, chronic pancreatitis (CP), and normal pancreas (NP). The model was trained and tested on a total of 1,174,461 EUS images. The sensitivity and specificity for differentiating AIP from NP were 99% and 98% respectively, for differentiating AIP from CP were 94% and 71% respectively, for differentiating AIP from PDAC were 90% and 93% respectively, and for differentiating AIP from all other groups (including PDAC, CP, and NP) were 90% and 85% respectively. These results demonstrate that the EUS-CNN model can aid in the diagnosis of AIP.

Ultrasonography serves as the primary modality for the assessment of cholelithiasis and cholecystitis. However, its sensitivity is limited, leading to potential misdiagnosis in cases of acute cholecystitis[37],In order to address this challenge, Yu et al[38] have developed an auxiliary diagnostic system based on deep learning techniques, which is named as SSD-FPN-ResNet-50 and MobileNet V2. This system aims to detect and localize gallstones by utilizing static ultrasound images acquired by medical professionals or technologists for initial diagnosis of acute cholecystitis. The SSD-FPN-ResNet-50 model achieved an AUC value of 0.92 for the identification of gallstones, while the MobileNet V2 model achieved an AUC value of 0.94 for the diagnosis of cholecystitis. The implementation of machine learning algorithms in the abdominal ultrasound image analysis demonstrated satisfactory detection performance and efficiency.

3.2 Prediction

3.2.1 Complication prediction

Acute pancreatitis (AP) is a common acute abdominal condition, with most AP patients having a mild course that can recover within a week. Approximately 20% of patients may develop severe complications. Moreover, the prognosis of AP patients who experience severe complications is poor, thus early detection and prompt management of AP-related complications are of utmost importance.

Qu et al[39] utilized diverse machine learning algorithms, including decision trees (CART), random forests (RF), support vector machines (SVM), and extreme gradient boosting (XGBoost), to establish a predictive model for acute kidney injury (AKI) in patients with acute pancreatitis. They compared the predictive performance of these algorithms with the classical multivariate logistic regression (LR) method. Among the four machine learning algorithms, XGBoost demonstrated superior performance, with its predictive performance surpassing that of traditional LR methods, with an AUC of 91.93%, the highest sensitivity of 61.9%, specificity of 88.5%, and accuracy of 86.31%. These results indicate that the use of machine learning algorithms in predictive models can assist clinicians in early AKI prediction and potentially prevent further renal damage.

Fei et al[40]constructed a risk and severity prediction model for acute respiratory distress syndrome (ARDS) following severe acute pancreatitis (SAP) based on neural network algorithms. The ANNs predictive model demonstrated a sensitivity of 87.5% and an accuracy of 84.43% in recognizing ARDS risk. They also identified pancreatic necrosis, lactate dehydrogenase, and arterial oxygen saturation as the most important independent variables. The ANNs predictive model exhibited good accuracy of 73.1% in overall severity prediction of ARDS. These findings suggest that the ANNs predictive model is a valuable tool for ARDS risk prediction and can extract informative ARDS risk factors.

ISSN 2616-5791 Vol.4, Issue 12: 27-34, DOI: 10.25236/AJMHS.2023.041204

Fei et al[41] employed an artificial neural network (ANN) to establish a predictive model for the formation of portal-splenic-mesenteric venous thrombosis (PSMVT) in patients with acute pancreatitis, and compared its predictive ability with that of logistic regression. The ANNs model demonstrated a sensitivity of 80%, specificity of 85.7%, and accuracy of 83.3% for the identification of PSMVT, displaying different parameters compared to the logistic regression model. The area under the receiver operating characteristic curve was 0.849 (95%CI: 0.807-0.901) for the ANNs model, which outperformed the logistic regression model (AUC = 0.716)(95%CI: 0.679-0.761) in terms of overall performance. These findings suggest that the ANNs model is more accurate than logistic regression.

3.2.2 Disease risk prediction

Some diseases, especially cancer, are often discovered in the late stage, which increases the difficulty of treatment, and has a low cure rate and high mortality. Therefore, accurately predicting the risk of disease occurrence and timely intervention for high-risk populations hold significant importance in saving lives.

Severe acute pancreatitis (SAP) has a poor prognosis and high mortality compared to mild and moderate-severe acute pancreatitis. Early identification of high-risk individuals is crucial for reducing mortality rates and improving prognosis. Sun et al[42] developed a machine learning prediction model (APSAVE) based on routine clinical test results using the random forest algorithm to stratify the severity of acute pancreatitis (AP). APSAVE has a sensitivity of 74.1%, specificity of 72.7%, and AUC = 0.73. To further evaluate the accuracy of APSAVE, the authors used three commonly used clinical SAP prediction systems: APACHE II, BISAP, and Ranson's Criteria to classify the validation cohort and compared the classification results with APSAVE. The results showed that APSAVE and Ranson's Criteria had the highest accuracy in classifying the validation cohort, with AUCs of 0.73 and 0.74 respectively. APSAVE demonstrated higher sensitivity in predicting SAP cases, indicating that APSAVE is more effective in detecting early-stage SAP cases compared to the other three systems.

Pancreatic cancer is one of the most lethal malignancies due to difficulties in early diagnosis. Most patients are already in an unresectable and incurable state at the time of diagnosis[43].Studies have shown that type 2 diabetes mellitus (T2DM) patients are more likely to develop pancreatic cancer[44],Hsieh et al[45] constructed a machine learning prediction model based on logistic regression (LR) and artificial neural network (ANN) algorithms to predict pancreatic cancer risk in the T2DM population. The weighted k-fold cross-validation accuracies (k=10) of the LR and ANN models were 0.996 and 0.907 respectively. The areas under the ROC curve for all data were 0.727 and 0.605 respectively. The conclusion suggests that the LR model achieved better results in pancreatic cancer prediction compared to the ANN model, and utilizing the LR model can appropriately predict the risk of pancreatic cancer.

3.2.3 Prediction of treatment outcomes

Currently, there is still a considerable amount of research on machine learning techniques for predicting treatment outcomes. Predicting the treatment outcomes of patients in advance can help in selecting appropriate treatment plans and providing targeted therapies to improve patient prognosis.

Unscheduled follow-up visits for outpatients are often encountered in patients with acute abdomen. Due to the multidisciplinary nature and complexity of acute abdomen, it is not possible to achieve accurate diagnosis for all patients. Hsu et al[46] constructed a prediction model based on five machine learning algorithms, namely logistic regression (LR), support vector machine (SVM), random forest (RF), extreme gradient boosting (XGB), and voting classifier (VC). They used these algorithms to predict unscheduled revisit within 72 hours for emergency department patients with abdominal pain, and compared the predictive performance of the models constructed by each algorithm. The final results showed that the voting classifier (VC) had the best predictive performance, with an accuracy of 0.86, specificity of 0.89, sensitivity of 0.39, and an AUC value of 0.74. The prediction model built by the VC algorithm had good predictive performance, which can assist clinicians in making correct medical decisions.

Approximately 20% of stage IIA colon cancer patients will experience recurrence after surgery. Peng et al[47] developed a scoring system based on an artificial neural network (ANN) model to predict the 10-year survival outcome of patients with colon cancer after surgery. The authors constructed four prediction models based on different predictive indicators using the ANN. Model 4 integrated all the important clinical indicators and biomarkers identified in Models 1, 2, and 3. Pathological staging, TGFBR2, TGF-β, MAPK, pin1, β-catenin in tumor tissue, and TGF-β in normal mucosa were ultimately determined as important prognostic factors. Model 4 was closely related to the 10-year

ISSN 2616-5791 Vol.4, Issue 12: 27-34, DOI: 10.25236/AJMHS.2023.041204

survival outcome, with a sensitivity of 92.3%, specificity of 93.3%, and an overall accuracy of 93.1%. According to the scoring system developed, patients were divided into three subgroups: high risk, moderate risk, and low risk. The 10-year overall survival rates of the three subgroups were 16.7%, 62.9%, and 100% respectively ($P < 0.001$), while the 10-year disease-free survival rates (DFS) were 16.7%, 61.8%, and 98.8% respectively ($P < 0.001$). The study results indicate that this scoring system for stage IIA colon cancer can help predict long-term survival rates and identify high-risk individuals for more aggressive treatment.

4. Conclusion

In terms of assisting the diagnosis of acute abdomen, although there were many studies in the period from the 1970s to the 1990s regarding the high accuracy of computer-aided diagnosis in acute abdomen, computer-aided diagnosis acute abdomen is still not widely used. There have been few studies on assisted diagnosis in this field in the past 20 years, and the reasons for this may include the following points: 1. Lack of a large amount of prospective data for accurate validation of assisted diagnosis model. Scholars who have conducted verification have been unable to replicate the high accuracy reported in other studies, which has led to questioning of the high accuracy of relevant research; 2. It is difficult to control the quality of the data. Twenty years ago, the electronic medical record system was not fully popularized, resulting in the missing of necessary data; 3. Due to the limitations of computer models, theories, and computing power 20 years ago, researches on assisted diagnosis in this field has stagnated; 4. Acute abdomen involves a wide range of disciplines and is a complex disease. The accuracy of computer-aided diagnosis results obtained solely based on chief complaints, physical signs, symptoms, and other data is not high. Compared with the assisted diagnosis of all diseases in the field of acute abdomen, the machine learning identification of specific acute abdomen diseases, such as pancreatitis, appendicitis, gallstone, celiac disease, and other common acute abdomen diseases, has achieved good results through the analysis of general information, laboratory tests, imaging data, etc. It can improve the diagnosis efficiency and accuracy of specific acute abdomen diseases. In terms of disease prediction, studies have shown that the application of machine learning in the field of acute abdomen prediction has achieved excellent predictive results in complication prediction, disease risk prediction, and treatment outcome prediction, playing an important role in improving diagnosis and treatment efficiency and reducing clinical burden.

With the comprehensive popularization of electronic medical records nowadays, patient records have been digitized and a massive amount of medical data has been stored. This wealth of data can be harnessed, and one major advantage of machine learning lies in its capacity to analyze large quantities of complex data in a short period of time. However, its limitations are apparent. On one hand, machine learning relies heavily on data analysis and is highly dependent on the quality and accuracy of the data. If the data is of low quality or contains biases, it can lead to a decrease in the accuracy. On the other hand, different machine learning models exhibit varying levels of accuracy in diagnosing and predicting outcomes when analyzing different datasets. Each machine learning model has its own strengths, and it is crucial to select the optimal model based on the specific dataset being analyzed. In recent years, the surge in digital information in the medical field has led to improvements in the quality of medical data, coupled with advancements in the data analysis capabilities of machine learning. The integration of big data with machine learning is poised to become a new research direction in the field of acute abdomen. With the further deepening of machine learning research in acute abdomen, it is believed that the challenges faced in machine learning-assisted diagnosis of comprehensive acute abdomen will be overcome. Through clinical validation, machine learning can be further applied in clinical practice, providing assistance in the diagnosis and risk prediction of acute abdomen.

References

[1] Laméris W, van Randen A, van Es H W, et al. Imaging strategies for detection of urgent conditions in patients with acute abdominal pain: diagnostic accuracy study[J]. BMJ, 2009, 338:b2431.
[2] Macaluso C R, McNamara R M. Evaluation and management of acute abdominal pain in the emergency department[J]. Int J Gen Med, 2012,5:789-797.
[3] Kucukkartallar T, Cakir M, Tekin A, et al. Estimation of the capacity of emergency surgery in Konya: Nine-year multicenter study[J]. Turkish Journal of Surgery, 2016,32(4):252-255.
[4] Hustey F M, Meldon S W, Banet G A, et al. The use of abdominal computed tomography in older ED patients with acute abdominal pain[J]. Am J Emerg Med, 2005,23(3):259-265.

ISSN 2616-5791 Vol.4, Issue 12: 27-34, DOI: 10.25236/AJMHS.2023.041204

[5] Lewis L M, Banet G A, Blanda M, et al. Etiology and clinical course of abdominal pain in senior patients: a prospective, multicenter study[J]. J Gerontol A Biol Sci Med Sci, 2005,60(8):1071-1076.
[6] LIU X S, ZHANG X Y. Management principles of pregnancy complicated with surgical acute abdomen[J]. Chinese Journal of Practical Gynecology and Obstetrics, 1999(08):55-56.
[7] YANG Z H, ZHANG C M. Acute abdomen in children [J]. Chinese Journal of Practical Pediatric Clinical Practice,2018,33(06):418-421
[8] GUO R F, LI J L et al. Epidemiological survey of pre hospital emergency patients in Haishi City in 2007[J]. Chinese Journal of Emergency Medicine,2008(11):1127-1130.
[9] Stoker J, van Randen A, Laméris W, et al. Imaging patients with acute abdominal pain[J]. Radiology, 2009,253(1):31-46.
[10] Marincek B. Nontraumatic abdominal emergencies: acute abdominal pain: diagnostic strategies [J]. Eur Radiol, 2002,12(9):2136-2150.
[11] Gutierrez M, Veronez C L, Rodrigues V S, et al. Unnecessary Abdominal Surgeries in Attacks of Hereditary Angioedema with Normal C1 Inhibitor[J]. Clin Rev Allergy Immunol, 2021,61(1):60-65.
[12] ZHU C F, HOU X K, TAO Y et al. Clinical application and misdiagnosis reasons of emergency ultrasound diagnosis of elderly acute abdomen [J]. Chinese Journal of Gerontology, 2016,36 (12): 3011-3012
[13] LIU H Q, HAO M, WANG Y H et al. A 10-year retrospective summary and misdiagnosis analysis of patients with acute abdomen during pregnancy [J].China Health Statistics, 2014,31 (03): 515-517
[14] GU Z, LU X D, LU Q S et al. Analysis of 44 cases of misdiagnosis of acute appendicitis in gynecological acute abdomen [J] Chinese Journal of Practical Surgery, 2009,29 (S1): 137-138
[15] ZHENG J Z. Clinical analysis of 63 cases of atypical acute abdomen misdiagnosed as acute appendicitis [J] Shandong Pharmaceutical, 2008 (28): 98-99
[16] Hamet P, Tremblay J. Artificial intelligence in medicine[J]. Metabolism, 2017,69:S36-S40.
[17] Tang K J W, Ang C K E, Constantinides T, et al. Artificial Intelligence and Machine Learning in Emergency Medicine[J]. Biocybernetics and Biomedical Engineering, 2021,41(1):156-172.
[18] ZHAO X Q, LIU Y, PENG R et al. The clinical application of artificial intelligence in imaging examination of acute abdomen [J] China Digital Medicine, 2020,15 (11): 33-35
[19] Cornet G. Robot companions and ethics a pragmatic approach of ethical design[J]. J Int Bioethique, 2013,24(4):49-58, 179-180.
[20] Deo R C. Machine Learning in Medicine[J]. Circulation, 2015,132(20):1920-1930.
[21] ZHOU Z H.Machine Learning [M] Beijing: Tsinghua University Press, 2016
[22] Shepherd J A. Computer-aided diagnosis of acute abdominal pain[J]. Br Med J, 1972, 2(5809): 347-348.
[23] Khumrin P, Ryan A, Judd T, et al. Diagnostic Machine Learning Models for Acute Abdominal Pain: Towards an e-Learning Tool for Medical Students[J]. Stud Health Technol Inform, 2017, 245: 447-451.
[24] McAdam W A, Brock B M, Armitage T, et al. Twelve years' experience of computer-aided diagnosis in a district general hospital[J]. Ann R Coll Surg Engl, 1990,72(2):140-146.
[25] de Dombal F T, Matharu S S, Staniland J R, et al. Presentation of cancer to hospital as 'acute abdominal pain'[J]. Br J Surg, 1980,67(6):413-416.
[26] Wilson D H, Wilson P D, Walmsley R G, et al. Diagnosis of acute abdominal pain in the accident and emergency department[J]. Br J Surg, 1977,64(4):250-254.
[27] Papadopoulos H G A V V. Reliable diagnosis of acute abdominal pain with conformal prediction[J]. Engineering Intelligent Systems, 2009,17(2):127.
[28] LANG J H. Gynecological acute abdomen [J] Chinese Journal of Obstetrics and Gynecology, 2022,57 (03): 161-163
[29] Walmsley G L, Wilson D H, Gunn A A, et al. Computer-aided diagnosis of lower abdominal pain in women[J]. Br J Surg, 1977,64(8):538-541.
[30] Wilk S, Słowiński R, Michałowski W, et al. Supporting triage of children with abdominal pain in the emergency room[J]. European Journal of Operational Research, 2005,160(3):696-709.
[31] Tenório J M, Hummel A D, Cohrs F M, et al. Artificial intelligence techniques applied to the development of a decision–support system for diagnosing celiac disease[J]. International Journal of Medical Informatics, 2011,80(11):793-802.
[32] Reismann J, Romualdi A, Kiss N, et al. Diagnosis and classification of pediatric acute appendicitis by artificial intelligence methods: An investigator-independent approach[J]. PLoS One, 2019,14(9):e222030.
[33] Park J J, Kim K A, Nam Y, et al. Convolutional-neural-network-based diagnosis of appendicitis via CT scans in patients with acute abdominal pain presenting in the emergency department[J]. Sci Rep, 2020,10(1):9556.

[34] Mashayekhi R, Parekh V S, Faghih M, et al. Radiomic features of the pancreas on CT imaging accurately differentiate functional abdominal pain, recurrent acute pancreatitis, and chronic pancreatitis[J]. Eur J Radiol, 2020,123:108778.

[35] Si K, Xue Y, Yu X, et al. Fully end-to-end deep-learning-based diagnosis of pancreatic tumors[J]. Theranostics, 2021,11(4):1982-1990.

[36] Marya N B, Powers P D, Chari S T, et al. Utilisation of artificial intelligence for the development of an EUS-convolutional neural network model trained to enhance the diagnosis of autoimmune pancreatitis[J]. Gut, 2021,70(7):1335-1344.

[37] Matsui Y, Hirooka S, Kotsuka M, et al. Prognosis in Patients With Gallbladder Edema Misdiagnosed as Cholecystitis[J]. JSLS, 2019,23(2).

[38] Yu C J, Yeh H J, Chang C C, et al. Lightweight deep neural networks for cholelithiasis and cholecystitis detection by point-of-care ultrasound[J]. Comput Methods Programs Biomed, 2021, 211: 106382.

[39] Qu C, Gao L, Yu X Q, et al. Machine Learning Models of Acute Kidney Injury Prediction in Acute Pancreatitis Patients[J]. Gastroenterol Res Pract, 2020,2020:3431290.

[40] Fei Y, Gao K, Li W Q. Prediction and evaluation of the severity of acute respiratory distress syndrome following severe acute pancreatitis using an artificial neural network algorithm model[J]. HPB (Oxford), 2019,21(7):891-897.

[41] Fei Y, Hu J, Li W Q, et al. Artificial neural networks predict the incidence of portosplenomesenteric venous thrombosis in patients with acute pancreatitis[J]. J Thromb Haemost, 2017, 15(3):439-445.

[42] Sun H W, Lu J Y, Weng Y X, et al. Accurate prediction of acute pancreatitis severity with integrative blood molecular measurements[J]. Aging (Albany NY), 2021,13(6):8817-8834.

[43] Stathopoulos G P, Androulakis N, Souglakos J, et al. Present treatment and future expectations in advanced pancreatic cancer[J]. Anticancer Res, 2008,28(2B):1303-1308.

[44] Carreras-Torres R, Johansson M, Gaborieau V, et al. The Role of Obesity, Type 2 Diabetes, and Metabolic Factors in Pancreatic Cancer: A Mendelian Randomization Study[J]. J Natl Cancer Inst, 2017,109(9).

[45] Hsieh M H, Sun L M, Lin C L, et al. Development of a prediction model for pancreatic cancer in patients with type 2 diabetes using logistic regression and artificial neural network models[J]. Cancer Manag Res, 2018,10:6317-6324.

[46] Hsu C C, Chu C J, Lin C H, et al. A Machine Learning Model for Predicting Unscheduled 72 h Return Visits to the Emergency Department by Patients with Abdominal Pain[J]. Diagnostics (Basel), 2021,12(1).

[47] Peng J H, Fang Y J, Li C X, et al. A scoring system based on artificial neural network for predicting 10-year survival in stage II A colon cancer patients after radical surgery[J]. Oncotarget, 2016,7(16):22939-22947.