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The Use of Artificial Intelligence Models for Predicting the Dynamics of Acute Pancreatitis Progression

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Abstract. Machine learning models are increasingly being employed to predict the dynamics of acute pancreatitis progression. Traditional methods utilising scales based on predefined parameters have limited applicability in processing all potentially important patient parameters with acute pancreatitis. ***The aim of this review*** was to examine the use of artificial intelligence for predicting the progression of acute pancreatitis, assessing complications and organ failure, determining the need for surgical interventions, and predicting mortality. ***Method.*** This is a narrative study that explored the use of artificial intelligence and machine learning methods for predicting the progression of acute pancreatitis. PubMed® and Google Scholar were searched using keywords such as «machine learning acute pancreatitis», «deep learning acute pancreatitis», «artificial intelligence acute pancreatitis», «artificial neural networks acute pancreatitis» and «machine learning acute pancreatitis — complications forecasting». ***Results.*** Recent studies have investigated the use of artificial intelligence models for predicting the progression of acute pancreatitis. These studies confirm the effectiveness of machine learning in handling large datasets. Machine learning models can identify patient complications, assess the need for surgical intervention, and predict mortality. Radiomics also shows promise as an auxiliary tool for assessing local changes in patients with acute pancreatitis. ***Conclusion.*** The use of various machine learning models, such as random forests, recurrent neural networks, and deep learning algorithms, allows accurate identification of risks and enhances the clinical management of acute pancreatitis. Exploring nonobvious interactions with ML tools for assessing systemic changes and individual criteria will expand the ability to determine treatment tactics and surgical interventions.

Key words: artificial intelligence, infectious complications, machine learning, mortality, multiple organ failure, operative pancreatic debridement timing, pancreatitis acute necrotizing, prognosis, radiomics.

Introduction

Machine Learning (ML) is a field of computer science that investigates and develops models using algorithms that perform well-defined tasks based on data analysis. ML relies on algorithms that incorporate rules or patterns for analysis.

Models based on ML algorithms have experienced unprecedented breakthroughs in data analysis over the past decade. The success of artificial intelligence (AI) in medicine has become possible due to the significant increase in computational power, the demand from large corporations and the availability of data, particularly with the widespread adoption of electronic medical records (EMRs) by hospitals. AI models utilising ML algorithms are actively used for identifying disease-specific biomarkers. Several AI models have demonstrated effectiveness in predicting the occurrence of gastrointestinal disease complications [1], including liver failure [2], sepsis [3] and other conditions.

Acute pancreatitis (AP) is one of the most common gastrointestinal diseases. While mild AP occurs in approximately 80% of patients and has a favorable course, severe acute pancreatitis (SAP) is characterised by concomitant complications, organ failure (OF) and mortality ranging from 6.1% to 30% [4, 5]. Patients with AP undergo a broad spectrum of examinations. Evaluating the condition, disease dynamics and prognosis requires analysing these extensive data. Unlike traditional approaches and techniques that may not adequately assess and interpret data, ML allows for a comprehensive analysis of patient records, visualisation of data and the results of clinical and laboratory tests. The use of ML algorithms opens up opportunities to discover new nonobvious interactions, including those occurring over time or depending on the correlation of parameter values. Additionally, ML models can compensate for the lack of variables in "input" data processing, thereby improving the accuracy, specificity and prognostic value of the models.

This review aimed to substantiate the use of ML in predicting AP progression, assessing the dynamics of complications and OF, determining the need for surgical interventions and determining mortality.

Method

This narrative study explored the use of AI and ML methods for predicting the progression of acute pancreatitis. PubMed® and Google Scholar were searched using keywords such as «machine learning acute pancreatitis», «deep learning acute pancreatitis», «artificial intelligence acute pancreatitis», «artificial neural networks acute pancreatitis» and «machine learning acute pancreatitis — complications forecasting». Additionally, specific ML models, such as «recurrent neural network», «XGBoost» and «naive Bayes» were included. Special attention was given to sources that focused on predicting complications, OF, the timing of surgical interventions, and assessing mortality risk in AP patients.

Assessment of local changes using the ML models with visualisation

Currently, research is actively being conducted on the automatic identification of the individual structures of the pancreas in both 2D and 3D visualisation formats. Although current artificial neural network models have the ability to analyse data only approximately to the level of an expert's opinion, with each passing year, the architecture of ML models continues to improve [6].

Radiomics involves transforming visualisation data into high-dimensional objects that can be used to obtain biomarkers for the classification and prediction of diseases, which in some cases can be assessed more accurately and earlier than when processed by an expert [7]. In pancreatology, radiomics is used as an auxiliary tool or automated interpreter of radiological images, where AI can generate accurate and reproducible visual diagnoses, reducing the workload on physicians. Several studies have demonstrated the advantages of radiomics as a promising direction for predicting oncological processes in the pancreas [8, 9]. AI can provide automatic or semiautomatic segmentation and registration of the pancreas and its lesions. These solutions have been applied to various visualisation methods commonly used for diagnosing liver and pancreatic diseases, such as ultrasound, endoscopic ultrasound, computed tomography (CT), magnetic resonance imaging and positron emission tomography/CT.

Several studies have demonstrated the role of visceral adipose tissue in predicting OF, SAP and pancreatic necrosis [10, 11]. Visceral adipose tissue has been demonstrated to outweigh body mass index in predicting the severity of AP [12]. Fat adjacent to acinar tissue is associated with damage to the pancreas parenchyma in AP. Fat in the pancreas has a direct toxic effect on surrounding tissues in AP [13].

Yang et al. optimised ConvNet with a naive Bayes model and demonstrated that the quantitative determination of the pancreatic fat fraction reached expert-level accuracy [14]. In the study by Janssens et al., 3D iterative decomposition with echo asymmetry and least squares estimation (IDEAL) MRI was used to determine the proton density fat fraction for each pancreatic slice. A convolutional neural network based on the UNet architecture was trained to autonomously determine the proton density fat fraction to calculate the parameters for the entire pancreas. The average proton density fat fraction had a strong inverse correlation with the mean Hounsfield unit without contrast-enhanced CT, demonstrating the effectiveness of the methodology for assessing pancreatic obesity [15].

The use of ML to determine the window needed for decision-making in APs

Luo et al. proposed a deep learning model based on a recurrent neural network (RNN) for individually predicting the timing of surgical intervention for necrotising pancreatitis (AUC=0.71). A seven-day time window is the best prediction interval since, if the frequency of monitoring laboratory tests is low according to EMR data, it cannot be accurately used for forecasting in a narrow window, and some laboratory indicators may undergo significant value changes over one week, complicating precise predictions in an excessively long window [16]. Additionally, a decision tree model was suggested (based on the presence of pleural effusion, HCT value, K value, and blood serum amylase level), which predicted the need for surgical intervention with 67.56% accuracy [17].

The criteria for potential outcomes

Predictions of complications

Existing models for predicting complications in AP patients are underutilised by surgeons due to their complexity, lack of integration with clinical workflows, delay of 24 hours or more for score calculation and limited understanding of how risk prediction can be used to improve outcomes.

Complications related to respiratory function play a significant role in disease dynamics. Predicting acute lung injury (ALI) using artificial neural network (ANN) [18] and logistic regression (LR) models for SAP [19] patients demonstrated high accuracy compared to traditional scales. Accurate predictions were obtained for acute respiratory distress syndrome (ARDS) in SAP patients using ANN models [20] and naive Bayes models, among other ML models [21]. The XGBoost model showed the best performance (AUC=0.84) in ARDS prediction compared to the LR, random forest (RF), SVM and decision tree (DT) models [22]. Nomograms developed on the proposed models outperform the Ranson, SOFA, BISAP, etc., scales in terms of convenience and effectiveness [23].

A series of retrospective studies demonstrated high accuracy in predicting acute kidney injury (AKI) in AP patients. Models based on the extreme gradient boosting algorithms XGBoost [24], LR [25] and RF [26] showed high accuracy in identifying patient categories with potential AKI development. The RF model accurately predicts ARDS in patients with AP accompanied by AKI [27].

Infectious complications play a crucial role in AP progression. The gradient boosting decision tree model performed better at predicting sepsis development than did the other models. For predicting intra-abdominal infection, highly accurate models using ANNs, LRs and RFs have been proposed [28]. However, incorporating the APACHE II score, CTSI score for intra-abdominal pressure, hospitalisation in the intensive care unit (ICU) and severity level complicates the practical use of these models.

FireVoxel software for radiomic studies has been used to construct a 3D volume-of-interest (VOI) on multiple slices, and a histogram of voxel values within the VOI has been created. This model predicted the occurrence of new local fluid collections, pancreatic necrosis, venous thrombosis and arterial pseudoaneurysms [29].

A separate study was dedicated to assessing the prognosis of thrombocytopenia occurrence in patients with AP. The presence of thrombocytopenia significantly increases the risk of intraoperative and postoperative bleeding. A nomogram constructed using multifactorial logistic analysis demonstrated excellent prognostic effectiveness in identifying thrombocytopenia [30].

Chang et al. used the LightGBM and XGBoost models to predict mortality, length of stay in the intensive care unit (ICU) and sepsis incidence with better accuracy than did the BISAP model [31].

ANN models demonstrated high accuracy in predicting the prognosis of patients with hospital stays longer than 7 [32] and 8.4 [33] days. Models based on radiographic and laboratory data obtained upon hospitalisation.

The SMART-CT index included two components, namely, those found in the mCTSI and points specified by experts (pancreatic necrosis, number of clusters, cluster size, presence of gas in clusters, ascites, pleural effusion, celiac artery and liver steatosis). SMART-CT effectively predicted mortality, intensive care unit (ICU) stay, need for surgical intervention, hospitalisation duration ≥4 weeks, number of hospitalisations ≥2, intensive care unit stay ≥2 weeks, OF and multiorgan failure (MOF) and SAP. A model built using binomial LR was used to construct a nomogram [34].

Studies have shown that models based on MLs have better performance in terms of the area under the receiver operating characteristic (AUROC) curve, sensitivity and specificity than do individual scores from traditional systems for predicting complications in AP patients.

Predictions of OF

The 2012 revised Atlanta Classification recognises the presence of an OF accompanying an AP as a key characteristic of severe disease. Existing systems for defining OF based on clinical and biochemical parameters, scales and imaging-based assessment systems have been developed to identify groups of patients at risk of developing OF or clinically severe disease rather than to identify individual patients. In patients with AP, the varying number, type, and sequence of organ affects over time limit the possibility of an individualised approach to decision-making within a step-up stepwise treatment strategy. Discrepancies persist in the use of the degree of the OF assessment and biomarkers primarily used for their assessment. For example, in various studies assessing respiratory failure, criteria for ARDS or ALI have been used. Timely forecasting and assessment of the dynamics of OFs prevent the progression of complications and help surgeons determine appropriate step-up approaches for the treatment of patients with AP. To date, there are no universal, accurate or easy-to-use methods available for determining the dynamics of the course of AP in the early or late phases [35]. ML models are actively being studied for predicting OF in AP.

The use of the RF model based on five cytokines accurately predicted persistent OF in the early stages of AP within 24 hours of symptom onset. The accuracy of the 5-cytokine panel was significantly greater than that of each individual cytokine [36].

The multitask and time-aware gated recurrent unit RNN (MT-GRU) demonstrated superior results in predicting OF within the next 24 hours after hospitalisation in patients with AP [37].

The bidirectional encoder representations from transformers model, a deep learning natural language processing model for text records, showed good predictive ability in determining OF when processing EMR within the first 72 hours of hospitalisation [38].

The adaptive boosting (AdaBoost) model outperformed the other ML models in predicting MOF[39]. Additionally, the ANN model demonstrated high accuracy when using a smaller number of biomarkers for predicting MOF in patients with moderate to severe AP [40].

Death prognoses

Early detection of patients at high risk of mortality is extremely important for timely surgical intervention. Approximately one-fifth of patients with potentially fatal SAPs are misidentified using traditional assessment systems [35]. Ding et al. [41] used the Medical Information Mart for Intensive Care III (MIMIC-III) database to construct ML models to predict in-hospital mortality. Patients at high risk of death can be easily identified in the early stages of AP. ALT, total calcium, and WBC were identified as prognostic markers of mortality in acute pancreatitis. The prognostic efficacy based on the AUC was 0.769 for the ANN model, 0.607 for LR, 0.652 for the Ranson's criteria, and 0.401 for the SOFA score, respectively.

In another study, the ANN was able to accurately predict mortality from AP (accuracy: 97.5%, with a discriminative power of 3.58) and proved to be more accurate than the APACHE II scoring system (accuracy: 82.4%; with a discriminative power of 1.17; $p<0.01$) or the GS score at 48 hours (accuracy: 80.7%; with significant discriminative power, $p<0.01$) [42].

The most significant factors associated with patient mortality were identified as the modified Marshall score at hospitalization and the preoperative modified Marshall score. The combination of a Generative Adversarial Network (GAN) model with LR, SVM, and RF accurately assessed patient mortality at the early stage of surgical intervention. GAN-RF (0.99) and GAN-SVM (0.99) achieved better results in evaluating key factors than GAN-LR (0.90) [43].

The Gaussian Naive Bayes (GNB) [44] and XGBoost [45] models demonstrated greater accuracy than did the other ML models in predicting mortality in intensive care unit (ICU) patients with AP, and the ANN and LR models were compared with the Glasgow Coma Scale (GCS), Ranson, Multiple Organ Dysfunction Score and APACHE II scores [46].

ML models for evaluating indications for surgical interventions

Lan et al. assessed the risk of death based on the timing of surgical intervention in patients with AP complicated by infection and pancreatic necrosis. The RF model most accurately allowed for calculating the timing of surgical intervention, considering the mentioned mortality factors [43]. IL-6, infected necrosis, fever onset, and CRP were crucial factors for determining the timing of surgical intervention (either <4 or ≥4 weeks) in patients with necrotizing pancreatitis. The classified accuracy of RF (0.80) was higher than that of SVM (0.78) and LR (0.71). Thanks to modeling conducted by GAN, the classification accuracy for all three models was improved. GAN-RF (accuracy: 0.89) performed better than GAN-SVM (0.84) and GAN-LR (0.83) [43].

Discussion

For most studies, there is a lack of validation and prospective analysis of clinical data using ML models. The evaluation of EMR data to determine recommendations for infusion and predict thetiming and need for surgical intervention is a promising area for AI research. In this field, ethical issues related to the limited involvement of physicians in patient treatment need to be addressed [47].

Identifying surgical landmarks and strategies for surgical intervention are topics for further AI research. In this field, standardisation does not always reflect the current scenario during surgery. ML models that utilise multimedia data and potentially process surgical procedure videos require preprocessing «input» data. This is due to the lack of a unified system for recording surgical procedures. It is also essential for surgeons to understand the logic of «output» data, which may not always be interpretable with existing tools. In other words, if the process leading to a recommendation is not clear, the «output» data of the model are likely to be overlooked [48].

Conclusion

The utilization of ML in patients afflicted with acute pancreatitis is increasingly being scrutinized. Research endeavours pertaining to ML, specifically those concerning prognostication and the evaluation of acute pancreatitis dynamics, have showcased superior precision compared to conventional methodologies. Nonetheless, a lack of understanding regarding contemporary ML models, coupled with predispositions toward the perceived complexity of their application, impedes their integration into clinical practice. However, further research on ML models is needed to identify local complications of AP using radiomic models. Exploring nonobvious interactions with ML tools for assessing systemic changes and individual criteria will expand the ability to determine treatment tactics and surgical interventions.

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