Predicting Acute Biliary Pancreatitis Relapse using CNN: The MINERVA Multicentric Study

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INTRODUCTION

Acute pancreatitis (AP) is the main pancreatic disease diagnosed in the world [1]. The etiology of AP is commonly alcoholic or related to biliary events [2,3]. Current guidelines recommend performing early cholecystectomy (EC), as surgery significantly reduces the risks of subsequent recurrence [4,5,6,7,8]. Recurrence of acute biliary pancreatitis (RBAP) is defined as a syndrome of multiple distinct acute inflammatory responses originating in individuals with genetic, environmental, traumatic, metabolic, who experienced a second episode of AP after at least 3 months [9]. To date, RBAP is a dangerous clinical complication of the pancreas, requiring emergency surgery and it can cause death if not operated on within 24 hours of onset [9]. However, due to particular patient frailties, medical-surgical conditions, or logistic problems, EC is not always performed [10]. The early identification of patients at high risk of recurrence could lead to better clinical and logistics management and provide practical recommendations for cholecystectomy priority [11,12,13,14]. Predicting and preventing RBAP can reduce costs of hospitalization and medical care and, more importantly, promote the management and prioritization of cases hospitalized with AP and potentially subject to relapse. Our recent systematic review [15] confirmed that there are no prospective studies that tried to model the prediction of RBAP. All evidence emerged through monocenter, retrospective data, was inconclusive and contradictory. The aim of the MINERVA study is 2-fold: on one hand, it aims to gather prospective data about RBAP from XX centers in Italy; on the other, it aims to develop and validate the first machine learning-based predictive model to identify patients at risk of RBAP [16].

OBJECTIVE

The MINERVA (Machine learnINg for the rElapse Risk eValuation in Acute Biliary Pancreatitis) project is the first observational multicenter prospective trial designed to investigate the predictive factors of relapse in acute biliary pancreatitis using artificial intelligence (AI) and by collecting outcomes at 3 months, 6 months, and 1 year follow-up. The aim of this project is to develop a predictive model of acute biliary pancreatitis recurrence based on a convolutional neural network (CNN), using images generated from tabular clinical data from both prospective and retrospective multi-centric sources.

Methods Clinical tabular data from the retrospective MANCTRA [17] and prospective MINERVA [16] datasets were merged to obtain 2413 instances appropriately preprocessed to manage missing values, normalizations and prevent errors. A strong imbalance was regulated applying the adasyn algorithm [18], to increase the minority class (initially 8% of the total) with artificial instances. The final dataset was made by 3630 subjects divided in 1441 with relapse and 2189 without it. The selected predictors were divided in numerical: the patient's age, BMI, white blood cell (per mm3), neutrophil (per mm3), platelet (per mm3), international normalized ratio, protein c-valuesreactive, aspartate aminostrasferase (units/liter), alanine aminostrasferase (unit/liter), total birylubin (mg/dl), direct conjugated birylubin, gamma glutamyl transpeptidase (units/liter), serum amylase (units/liter), lipasis (units/liter), the lactate dehydrogenase (units/liter); and categorical: sex of the patient, previous episodes of pancreatitis, clinical history of diabetes, clinical history of chronic lung disease, hypertension, atrial fibrillation, chronic kidney disease, disease of the hematopoietic system, immunosuppressive drugs at the time of admission, cholodulelithiasis, acute cholangitis, department of hospitalization and Endoscopic Retrograde Colangiography-Pancreatography. Then, using the PCA-based Deepinsight algorithm [19], the

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features have been mapped to pixels with a grid size equal to 128; To process the images, we designed a CNN consisting of 3 reduction blocks with ReLU and MaxPooling activation, followed by 2 fully connected layers: the first with ReLU and Dropout, the second with sigmoid activation for binary classification (RBAP: yes/no). we used Adam optimizer (L2 adjustment) and binary cross-entropy loss. Data were divided into training (70%), validation (15%) and test sets (15%), and AUC, F1-score and accuracy were used for evaluation. We used an adaptive variable learning rate (LR) starting from 0.001, a batch size(BS) between 16 and 32, the number of periods incrementally validated according to a trial and error approach, and then fixed by early stopping (ES) technique. A classical non-parametric bootstrap approach, based on 50-iterations, was adopted to estimate the variability of performance metrics by evaluating greater robustness and reliability of the predictive capabilities compared to fluctuations in baseline data. The python code took about 30 minutes to run on a PC with Processor 12th Gen Intel(R) Core(TM) i5-12400F (12CPUs) 2.5 GHz, Operating System Microsoft Windows 11 Pro and RAM from 32GB, equipped with NVIDIA GeForce RTX 4060.

RESULTS

The model showed good predictive performance in validation phases with an AUC of (84.38 ± 1.76)%, while on test AUC is 82.25% . Parameters as follows: BS=32, LR=0.001, ES at 60 epochs and weight decay equal to 0.0001.

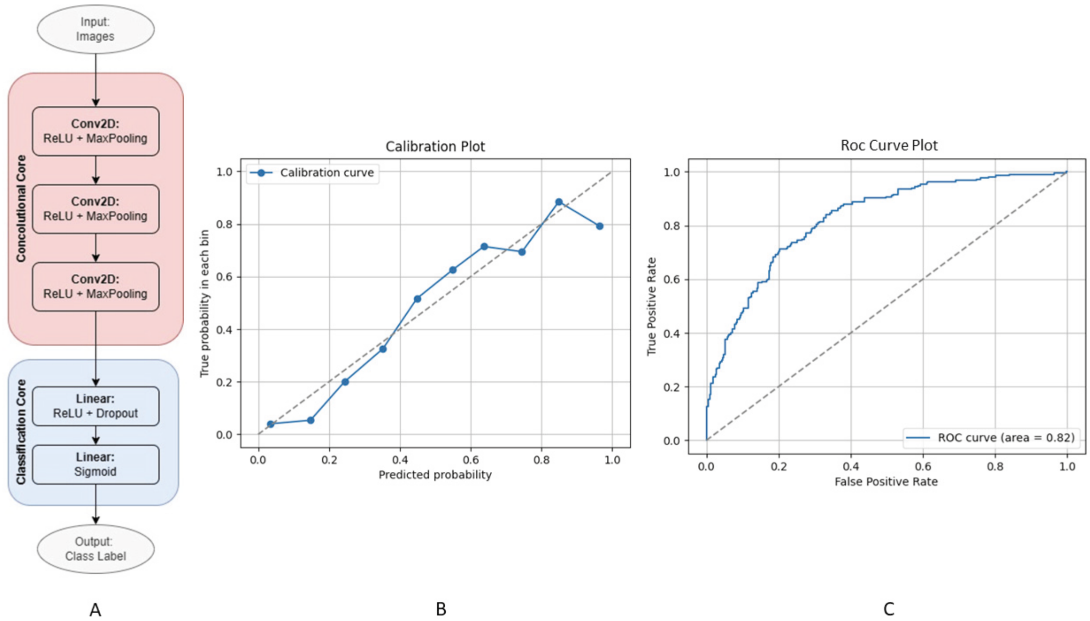

Figure 1. Structure of the implemented CNN (A), Calibration Plot (B) and Roc Curve Plot (C) of the model.

CONCLUSION

This study presents the first AI model developed specifically for the prediction of RBAP. The integration of clinical data from complementary sources and the application of CNN techniques demonstrate the feasibility and clinical potential of this approach in an area that has been little explored so far. The results of this work are promising and the testing of AI to support the management of cases of relapse of acute biliary pancreatitis can prove a beneficial factor in supporting the medical clinic.

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