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Review

The Role of Artificial Intelligence in Endoscopic Ultrasound for Pancreatic Diseases

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Abstract: The integration of artificial intelligence (AI) into healthcare, particularly in the field of gastroenterology, marks a significant advancement in the diagnosis and treatment of pancreatic disorders. This narrative review explores the application of AI in enhancing Endoscopic Ultrasound (EUS) imaging techniques for pancreatic pathologies, focusing on developments over the past decade. Through a comprehensive literature search across several scientific databases, including PubMed, Google Scholar, and Web of Science, this paper selects and analyzes 50 studies that highlight the role, benefits, precision rates, and limitations of AI in EUS. The findings suggest that AI not only improves the quality of endoscopic procedures, as acknowledged by a majority of gastroenterologists in the UK and USA, but also offers a promising future for medical diagnostics and treatment, potentially addressing the shortage of specialists and reducing morbidity and mortality rates. Despite AI's infancy in clinical applications and the ethical concerns regarding data privacy, its integration into EUS has enhanced diagnostic accuracy and provided minimally invasive therapeutic alternatives. This review underscores the necessity for further clinical data to evaluate the applicability and reliability of AI in healthcare, advocating for a collaborative approach between physicians and AI technologies to revolutionize the traditional clinical diagnosis and expand treatment possibilities in gastroenterology.

Keywords: AI; endoscopy; Endoscopic Ultrasound

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1. Introduction

Artificial Intelligence (AI) is a state-of-the-art tool for third-millennial society's routines, and the population is getting more comfortable using it. From personal assistants on smartphones to autonomous vehicles, it is present in many fields in the everyday life of each individual. Representing a problem-solving and learning form of intelligence, it found its way into the health system in the 1970s and, since then, healthcare has faced a transition to using new techniques based on machine learning (ML). AI can represent a real help within the specialties that deal with complex datasets and information [1]. It is also known for its image discrimination and classification. After overcoming the difficulties that might occur due to their lack of technical skills, physicians can learn to operate with doctor-friendly apps.

The gastroenterology domain is fighting its challenges with the help of AI, and certain procedures are enhanced by the use of robotics, mostly regarding precision and guidance [2].

In two surveys, 228 gastroenterologists from the UK and USA were interviewed about their opinions on AI in their field. Better quality of endoscopies was reported by 97% of UK specialists, while 84.7% of American doctors agreed that the machines improve endoscopic performance. The general concerns discussed were the costs, increased duration of the process, data availability, and the dependence on the operator's experience [3,4]. Stan-Ilie et al. [5] calls AI "the rising star" of the medical field, proving that it may be of great help to gastroenterology trainees. Endoscopic Ultrasound (EUS) is a highly sensitive technique whose role in pancreatic disorders has constantly been developing through a better diagnostic yield of small pancreatic malignancies than CT or MRI [6]. However, it has its limitations regarding chronic and acute pancreatitis.

Recently, EUS-guided methods have been used not only as diagnosis tools but also as minimally invasive therapeutic alternatives to surgery or radiology. This review aims to state how the gastroenterology field may benefit from the help of AI, more precisely, on its role in the endosonographic imaging for pancreatic disorders. It represents an extensive overview of what has been accomplished in the last 10 years and also tries to describe which are the downsides and risks of failure in computer-aided medicine.

2. Materials and Methods

This paper is a descriptive, narrative review that navigates through the realm of AI methods applied in the context of EUS. A meticulous medical literature review was conducted using scientific databases: Google Scholar, WebofScience, PubMed, Scopus, Wiley Online Library, and GIE Journal. The research began with PubMed, using the following search formula: (pancrea*) AND (artificial intelligence OR AI) AND (endoscopic ultrasound OR EUS OR endosonography). Subsequently, minor adjustments were made to ensure an adequate number of results. We have selected 52 relevant studies for our review, dating from 2013 to 2024. Only full-text articles were chosen, including original studies, reviews, and meta-analyses. Case presentations and editorials were excluded. When selecting the studies, the following inclusion criteria were taken into consideration: role and benefits of AI in EUS for pancreatic pathologies, precision rate (sensitivity and specificity) in AI technologies, and its limitations. Additionally, certain articles were chosen from other sources to supplement the data already collected and to explain some basic concepts behind AI techniques. All authors participated in the database search and exclusion criteria included studies about the role of AI in other pathologies or specialties (Figure 1).

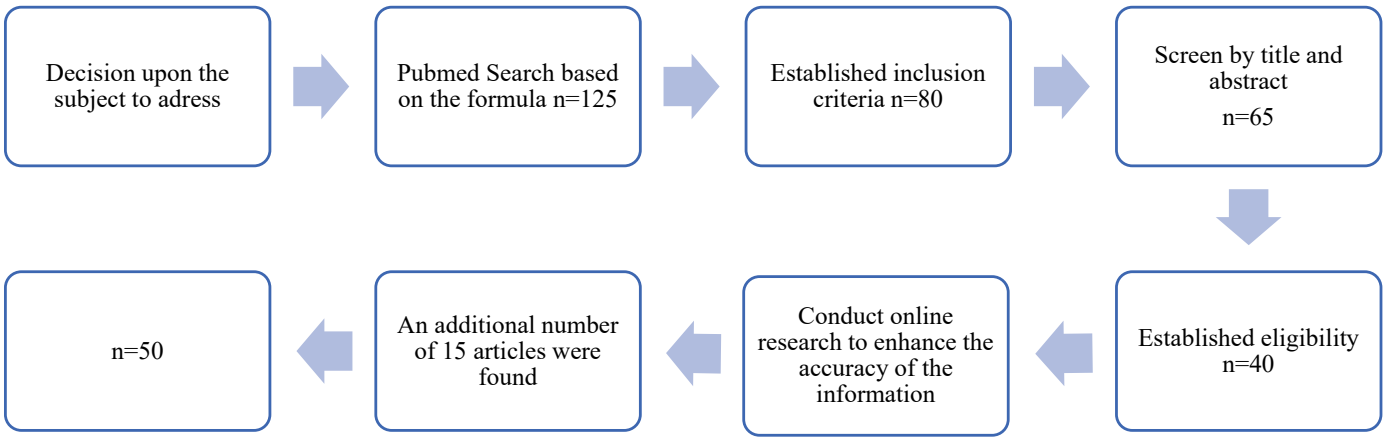

Figure 1. Search strategy.

3. Results

3.1. AI Methods in Pancreatic Pathology Diagnosis

Regarding pancreatic pathologies, the diagnosis might be performed using an AI system. It is of utmost importance that we understand how AI works. It is a tool that functions on certain algorithms such as the support vector machine (SVM), which is primarily used for classification. Machine learning (ML) works on a set of data gathered and organized by a human and it is trained to give results, improve performance, and reduce failure by running multiple times (Table 1).

Table 1. Description of artificial intelligence methods.

Artificial Intelligence Methods	
Neural Networks	Similar to a biological nervous system, it consists of overlapping layers of connected nodes
Deep Learning	Involves many layers of nonlinear information that are processed for information extraction, pattern analysis, and classification by using various neural networks
Machine Learning	A computer's ability to make decisions or to identify various patterns from specific data
Convolutional Neural Networks	Deep learning architecture that adapts the desired tasks and is used for the detection and recognition in images
Computer-aided Diagnosis	Used for identification or diagnosis of a specific object/region of interest based on a computer algorithm.
Support Vector Machine	Used for nonlinear problems; it uses a discriminative classifier that determines classes from a separating hyperplane

Human interpretation of images is prone to errors due to perception and cognition. Medical imaging is getting increasingly more complex and the human eye might lack the capacity of an artificial form of intelligence when it comes to small or subtle lesions. Hence, this may lead to skipping an important aspect of the diagnosis. A William Osler saying raises the request for innovation in the medical field: "Medicine is a science of uncertainty and an art of probability" [7]. The latest innovation in AI is deep learning (DL), which is based on convolutional neural networks (CNNs), a concept that imitates the human brain. One of the common things that run through CNNs is face recognition on one's smartphone [8] (Figure 2).

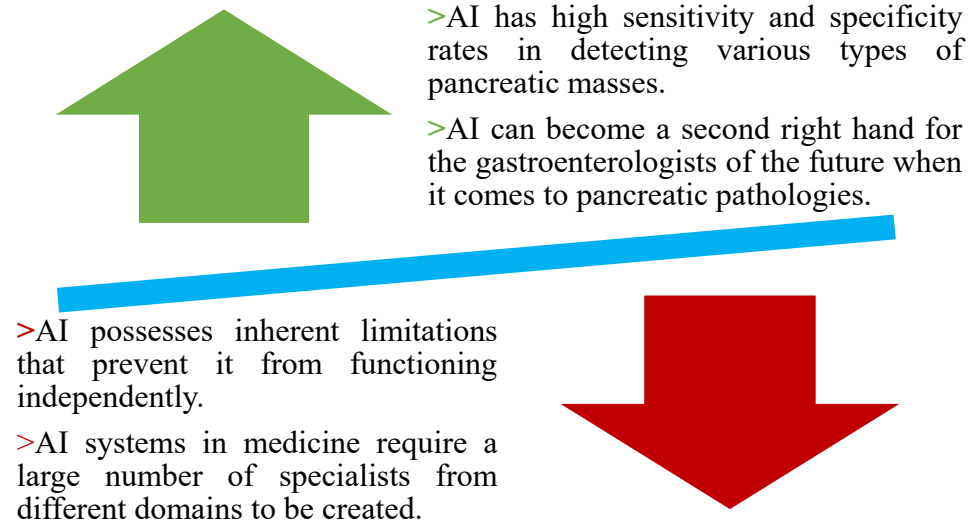

Figure 2. General summary of advantages and disadvantages of AI.

3.1.1. Chronic and Acute Pancreatitis

In two Chinese studies, it is stated that computer-aided diagnosis (CAD) for pancreatic disorders has given satisfying results since 2013 and it is highly accurate. In the first study, this non-invasive procedure has been used to differentiate chronic pancreatitis (CP) from pancreatic cancer (PC). It is mentioned that they created an SVM algorithm and included 126 CP patients and 262 PC patients in the model. After 200 trials, the results looked promising: overall sensitivity and specificity rates of 96.25 $\pm$ 0.4460% and 93.38 $\pm$ 0.2076%, respectively [9]. In the same manner, the other study proves the applicability of CAD in differentiating autoimmune pancreatitis from CP with slightly lower but significant sensitivity and specificity rates this time (84.1 $\pm$ 6.4% and 92.5 $\pm$ 3.3%) [10].

Hong et al. suggested that the ANN is more reliable when it comes to a complex and non-linear set of variables to determine the clinical outcomes of acute pancreatitis. They developed this model based on their patients' variables: age, hematocrit, serum levels of glucose, calcium, and blood urea nitrogen. Their results showed a sensitivity of 81.3%, and a specificity of 98.9%, and the ANN classified a total of 96.2% of patients correctly. The ANN was capable of creating such connections between the data that it led to high-performance diagnostic conclusions [11].

Idiopathic acute pancreatitis (IAP) should not be missed out in this section. Occult biliary lithiasis is the primary cause in a significant portion of cases of idiopathic acute pancreatitis. Recognizing this subgroup is crucial for preventing the recurrence of pancreatitis and ensuring accurate diagnosis, avoiding both overdiagnosis and underdiagnosis. An ML-based decision tool aimed at detecting biliary sludge and microlithiasis in patients with IAP was trained [12]. By using clinical and laboratory parameters from 218 patients, the model achieved an impressive accuracy of 84%. Subsequent validation in two independent cohorts further confirmed its precision, with an accuracy of 76%. This novel tool offers a promising approach for early identification and management of biliary-related pancreatitis, potentially enabling timely interventions to prevent recurrent episodes.

3.1.2. Auto-Immune Pancreatitis

Auto-immune pancreatitis (AIP) is a pathology that generates several issues: the high value of false-positive results after EUS, the variety of its clinical forms, and the resemblance to pancreatic ductal adenocarcinoma (PDAC) in medical imaging [13]. When dealing with AIP, clinicians need additional, more precise tools to set an optimal diagnosis and choose a pathway in the therapeutic process. Conventional neural networks (CNNs) are entities able to learn and extract very complex information and, as it shows, may differentiate between normal pancreas (NP), and different pathologies such as AIP, CP, and PDAC [14]. A CNN trained with 1,774,461 EUS images from a cohort of 585 patients proved to have a rather optimal diagnosis prediction. Occlusion heatmaps were also generated and used to aid CNNs. Although the highest sensitivity (99%) and specificity (98%) rates were reached in differentiating AIP from NP, overall results were also promising when used for PDAC as well. Overall sensitivity and specificity rates of 90% and 85%, respectively, were reported in differentiating between AIP and all other discussed pancreatic disorders.

3.1.3. Pancreatic Cancer

Recently, the medical literature has focused on the applicability of computer-aided medicine in PC, which is known for its low survival rates at 5 years (11%) [15]. Many studies address the need for more performant diagnostic tools, especially for differentiating PDAC from other pancreatic cancer types. EUS generates an overall sensitivity of 98% but a specificity of just 20%. This percentage demands change [16]. The goal is to decrease mortality rates linked to pancreatic cancer through early detection and precise lesion identification. With its robust data analysis capabilities and rapid result delivery, AI may support gastroenterologists in their battle against this deadly disease. A meta-analysis conducted in 2023 states that AI has high accuracy (95%) in predicting pancreatic cancer and a pooled sensitivity and specificity over 90% [17].

To enhance diagnostic accuracy, a study [18] conducted at the Kursk Regional Clinical Hospital employed EUS on 272 patients with pancreaticobiliary lesions. Among these, 40.1% were diagnosed with PC and 14.7% with CP. Utilizing reference sonograms, a hybrid fuzzy mathematical model was developed at South-West State University, enabling differential diagnosis between CP and PC. Statistical analysis showed an acceptable level of accuracy, offering promise for broader application.

There are many types of PC (pancreatic ductal adenocarcinoma, pancreatic adenosquamous carcinoma, acinar cell carcinoma, metastatic pancreatic tumor, neuroendocrine carcinoma, solid pseudopapillary neoplasm), and AI may be a useful tool to differentiate between them. While EUS-FNB enables the precise diagnosis, using AI may help orientate the physician on the future diagnosis. A DL model may be used to distinguish pancreatic carcinomas from non-carcinomatous lesions. By using 22,000 images from 933 patients, this model achieved a sensitivity of 94%, specificity of 82%, and accuracy of 91%. These results indicate that DL may be considered when distinguishing pancreatic carcinomas from other lesions, although external validation from a specialist is always needed [19].

In 2016, Okan et al. [20] developed an ANN for a group of 172 patients and proved that if the system runs on more specific data, it is less likely to make mistakes. At first, 332 endosonographic images (202 of cancer and 130 of non-cancer) were analyzed and from 122 identified features, 20 were chosen by two gastroenterology professionals to be included in the dataset. Moreover, the data were organized by age range, <40, 40–60, and >60, and the overall accuracy, sensitivity, and specificity were 90.73%, 88.83%, and 91.56%, respectively. The machine was then trained to run with the same data, without the age classification, and the results were less satisfactory (accuracy: 87.5%; sensitivity: 83.3%; specificity 93.3%). Thus, more specific datasets result in superior performance.

It is worth mentioning another prospective study that describes a Contrast-Enhanced Harmonic Endoscopic Ultrasound (CH-EUS) master system that includes two models, Model 1 (for real-time capture and segmentation) and Model 2 (for distinguishing benign from malignant pancreatic masses) developed using DL and random forest algorithms. Patients were enrolled and randomly assigned to undergo EUS-FNA with or without CH-EUS MASTER guidance. In this clinical trial, CH-EUS MASTER significantly outperformed endoscopists in diagnosing pancreatic masses, with an accuracy, sensitivity, and specificity of 93.8%, 90.9%, and 100%, respectively. Additionally, CH-EUS MASTER-guided EUS-FNA improved the first-pass diagnostic yield, guiding FNA in real time [21]. The early detection of solid pancreatic masses of CH-EUS is vital for effective treatment, but mastering CH-EUS may pose some challenges. In addressing these challenges, developing a DL CH-EUS diagnosis system, designed for the real-time capture and segmentation of solid pancreatic masses, might be a real help. A system was rigorously tested using a dataset of 4530 EUS images. Results indicated that the CH-EUS MASTER system significantly enhanced the accuracy and efficiency of pancreatic mass identification. The performance rate was assessed using intersection over union (IoU), a metric used to evaluate DL algorithms by estimating how well a predicted object matches the ground truth data. The perfect IoU is considered to be 1, but values over 0.5 are considered favorable. Trainees demonstrated an improvement in the average IoU from 0.80 to 0.87 and reduced the average time for lesion identification across pancreatic regions, AI representing a valuable tool for increasing EUS proficiency.

3.1.4. Pancreatic Cystic Lesions

Intraductal papillary mucinous neoplasms (IPMN) are precancerous lesions with high prevalence but low identification rates, so AI might play a pivotal role in their diagnostic and therapeutic management. A study including 206 IPMN-confirmed patients presents an ANN model based on 3970 images [22]. Features such as sex, age, symptoms, laboratory test results, and location of the lesions were included in the dataset. All patients had undergone pancreatic resection and were confirmed to have IPMN. Although there are some constraints to this research, like having a limited number of patients or having only one cancer center as a reference, the results are to be considered. Physician diagnosis

accuracy (56%) was surpassed by the ANN (94%). As for the sensitivity and specificity rates, the tendency is positive as well, both being over 90%. Moreover, a DL method using EUS images trained to differentiate between low-grade and high-grade/invasive carcinoma IPMN gave satisfactory results [23]. Training on 3355 images and testing on 1823, the model achieved a remarkable 99.6% accuracy in classification. Compared to standard guidelines, the DL model significantly outperformed, suggesting its potential for accurate histological outcome prediction in IPMN cases.

Besides IPMN, there are other types of pancreatic cyst lesions (PCLs): simple retention cysts, serous or mucinous cystic neoplasms, and pseudocysts. To be able to determine which line of treatment should be followed, a distinction between malignant and benign cysts should be made. Usually, high-spatial-resolution imaging techniques are used for inspection, some of them collected through EUS. On two datasets of 111 patients [24], a deep learning model based on U-net architecture (for precise segmentation) was trained using EUS images. U-net contains an encoder and a decoder for capturing and localizing the information. In addition, the decoder has an attention gate that ignores irrelevant parts of images and concentrates only on the significant ones. Regarding outcomes, the system, which benefited from high pixel accuracy, was able to distinguish the lesions in more than 96% of cases. The limitations discussed were related to the small number of patients and images. There might also be a problem imposed by contrast/brightness variations in the ultrasound image acquisition. The results and performance of the AI model depend on the skills of the person who practices it and also on the cyst itself, raising problems depending on its topographical and structural peculiarities.

The string sign is an indicator for mucinous pancreatic cysts and it occurs when a mucus-containing cyst is punctured and a viscous, string-like material is seen extending from the cystic wall to the EUS needle. Interpreting sequential cyst fluid results in excellent diagnosis sensitivity (93.8%) and specificity (85.7%) for differentiating mucinous from non-mucinous pancreatic cysts through this sign [25]. Mucinous cysts are more likely to develop into a malignancy. Taking into consideration some future studies based on a string sign algorithm, the diagnosis process can be facilitated.

However, it is difficult for specialists to find the right diagnosis for all types of cysts using cytology and carcinoembryonic antigen (CEA), these having low sensitivity rates (approximately 55%). By introducing input layers such as type of cyst, CA19-9, CA125, amylase, sex, and age in an AI model, it may learn to correlate fluid characteristics with clinical data and differentiate malignant from benign, having a high sensitivity in studies (95.7%) [26]. Thus, it can be a support system in the exclusion diagnosis of pancreatic neoplasia.

The number of accidentally detected asymptomatic patients having PCLs is on the rise. The high cancer risk they present imposes the need for early identification and diagnosis. EUS-guided needle-based confocal laser endomicroscopy (nCLE) allows effective in vivo examination of PCL [27,28]. The great disadvantage of this technique is its need for experimental specialists for its interpretation. Using 68 nCLE videos, other available videos from public sources, and 21,937 images, three CNNs were developed to use in PCL identification: manual designation, maximal rectangular, and a U-net algorithm [29]. The accuracy was 88.99% in CNN1, 73.94% in CNN2, and 76.12% in CNN3. The best recognized PCL was mucinous, the one with the highest cancer risk, hence demonstrating the usefulness of an AI algorithm. This study also proves the feasibility of using CNN to identify PCLs (Table 2).

Table 2. The use of AI and its methods for various pancreatic diseases.

	Key Role	Benefits	Precision Rates	Limitations of AI
Chronic and acute pancreatitis	ANNs are more reliable when it comes to a complex and non-linear set of variables	A helpful method to differentiate these from PC or AIP	Sensitivity over 80% Specificity over 90%	The algorithms need a large number of data, many patients, and many clinical situations to be included in their making so that it is ready to differentiate properly between pathologies
Autoimmune pancreatitis	CNNs are entities able to learn and extract very complex information	Better diagnosis for this challenging pancreatic disorder	Sensitivity over 90% Specificity over 85%	
Pancreatic cancer	ANNs work on a set of specific data, are very precise, and have a low chance of false positive results	Higher precision rates, especially when it comes to IPMN	Sensitivity over 80% Specificity over 90%	
Pancreatic cysts	U-net deep learning model can be used for precise segmentation	Better differentiation between malignant and benign	Sensitivity over 90% Specificity over 80%	

3.2. Cytopathological Confirmation of AI-Based Diagnosis

Udriștoiu et al. [30] developed a diagnostic prediction model that generates automatic diagnosis, using a CNN and long short-term memory (LSTM). The confirmation of the machine's precision was assessed by cytopathological analysis of EUS-FNA samples. CNA assumes that the data are independent of each other, while LSTM tries to find a connection between them and captures the dynamic features over time. The spatial features of the images obtained through EUS were extracted by CNN, while the temporal features were collected by LSTM. After merging them and using advanced software, the algorithm established the diagnosis. A total of 3660 images from only 65 patients with diagnoses of ductal adenocarcinoma, neuroendocrine tumor, and pseudo-tumoral pancreatitis were introduced. The final accuracy was surprisingly high: 98.26%.

Cytopathological studies can be used in identifying neoplastic cell clusters. By using rapid on-site evaluation (ROSE) from obtained EUS-FNA samples, pancreatic masses can be identified with higher rates of success when using a DL model [31]. Given the general lack of cytopathologists in hospitals, a system with high accuracy (over 90%) in the segmentation and identification of cell clusters is a tool from which any institution might benefit. However, when ROSE is not available due to a lack of resources, other systems may replace it. Recently, mathematical technologies for cytopathology in the recognition of pancreatic tissue have aroused curiosity among doctors and computer specialists. They do not need teaching data and complicated computing. They require converting medical images into structured datasets, ultimately generating a faster and more specific diagnosis. A study shows that using 120 randomized combinations of evaluation indices, high accuracies of over 70% were obtained [32].

Given the small amount of tissue that can be collected through EUS-FNA, concluding a ductal adenocarcinoma diagnosis may be problematic. Fine-needle biopsy EUS (EUS-FNB) is an acquisition technique that has similar diagnostic accuracy to EUS-FNA combined with ROSE [33]. It collects pancreatic samples with preserved architecture, offering the possibility of not only morphological but also immunohistochemical diagnosis [34].

Another study [35] addresses the need for improved diagnostic tools in the context of pancreatic cancer. With EUS-FNA or EUS-FNB recognized for their high accuracies, there remains a demand for enhanced diagnostic aids to support cytopathologists in accurately differentiating between benign and malignant pancreatic tissues. This research presents a novel approach combining hyperspectral imaging (HSI) coupled with CNNs for an advanced diagnostic algorithm. By capturing detailed HSI images of cytological specimens obtained through EUS-FNA, the CNN model, specifically the ResNet18-SimSiam architecture, demonstrated impressive performance metrics, achieving an accuracy of

92.04%, sensitivity of 93.10%, and specificity of 91.23%. Insights into the model's decision-making process highlight critical features of tumor cell nuclei as the key to differential diagnosis. In the same manner, another study [36] validates the effectiveness of an AI model, ROSE-AI, as a substitute for traditional ROSE. With a focus on specificity, the ROSE-AI model achieved high accuracy rates of over 80%. It demonstrated its potential to detect cancer cells effectively. These findings suggest the feasibility of employing AI to address the lack of cytopathologists and extend the availability of ROSE in healthcare institutions.

Isolated carcinoma components (ICCs) refer to small fragments of carcinoma found circulating in the bloodstream. Detecting ICCs is challenging due to their unique morphology. Additionally, certain ductal adenocarcinomas contain numerous ICCs alongside a scarcity of easily detectable cells, further complicating their identification. An AI device was trained using tissue samples and high quantities of blood and the outcomes looked positive: 94.17% accuracy, 93.02% sensitivity, and 97.06% specificity [37]. The notable result was the recognition of ICCs, which may raise many problems for pathologists. Therefore, there is a chance that a support system based on ML can improve histopathological diagnosis results. Furthermore, stereomicroscopic image recognition AI systems trained through contrastive learning might be very close to what the pathologists observe through macroscopic on-site evaluation. The model learns the correlation between the hematoxylin–eosin-stained images with core tissue images and detects the pixels corresponding to different masses. The concordance rate was obtained by using IoU, its value being 0.8, with performance being comparable to experienced pathologists [38].

A meta-analysis conducted in 2022 [39] states that from a total of eight studies regarding ductal adenocarcinoma diagnosed using AI, an overall pooled sensitivity and specificity rate was over 90%. A second meta-analysis from the same year, this time performed on 11 studies on pancreatic adenocarcinoma AI-assisted diagnosis presented 86% accuracy, 90.4% sensitivity, and 84% specificity [40]. Another set of 14 studies was meta-analyzed, showing a 92% diagnostic accuracy [41].

3.3. Successful Trials of Different AI Systems

CH-EUS is used as an additional tool for pancreatic tumor characterization. U-net may be trained to perform an automated classification of images and videos obtained through this intervention to avoid subjective analyzing and interpretation bias. In two academic centers, the National Taiwan University Hospital and Gifu University Hospital, a DL tool was created and used for the automatic segmentation of pancreatic solid malignant masses [42]. A total of 100 patients, men and women with ages between 29 and 89 years, with a certain verified diagnosis, were included in the algorithm. Only high-quality images were introduced in the algorithm, excluding the ones that presented unclear zones caused by respiratory movements or calcification of the tumor; thus, the study has its limitations. In addition, ultrasounds can present artifacts coming from movements, bone structures, digestive air, and other anatomic variations. The diagnoses taken into consideration besides pancreatic malignancy (PC, neuroendocrine tumor, metastatic pancreatic tumor, malignant lymphoma, and pseudopapillary neoplasm) were autoimmune pancreatitis, CP, fat necrosis, and mass-forming pancreatitis. The overall IoU was 0.77 (with a range between 0.39 and 0.91). Given this information, it might be concluded that the AI needs to have clear and accurate images to speed up the process of diagnosis. Its datasets need to be compiled using clear and precise information so the system performs rapidly. It remains a useful tool for specialists, being able to automatize the segmentation process and ease the diagnosis of pancreatic lesions that can be characterized (by size, shape, density, location, symptoms, histological characteristics, etc.).

A more recent study conducted by Tang et al. using a CH-EUS master trained with DL resulted in higher than 90% accuracy, sensitivity, and specificity rates [21]. They developed a diagnostic tool called CH-EUS MASTER, which enables real-time identification and tracking of pancreatic masses by describing the Time-Intensity Curve characteristics of different regions and pinpointing areas of interest for guidance. A randomized controlled

trial was conducted at a single center. Compared to the endoscopists' diagnosis, the AI system gave better results, with a total of 36 patients diagnosed correctly by the model, with only three errors, while the doctors misdiagnosed five. Due to their capacity to learn complex data, CNNs can limit human error (Table 3).

Table 3. A summary of the published studies so far on EUS and AI image recognition, based on their specificity, sensitivity, and diagnostic accuracy.

Author	Specificity	Sensitivity	Accuracy	AI Application
Zhu et al., 2013 [9]	94.2%	96.25%	93.38%	Differentiation between pancreatic cancer and chronic pancreatitis
J. Zhu et al., 2015 [10]	92.5%	84.1%	89.3%	Differentiation between autoimmune pancreatitis and chronic pancreatitis
W. D. Hong et al., 2013 [11]	90%	85%	87.5%	Prediction of persistent organ failure in acute pancreatitis
S. Sirtl et al., 2023 [12]	89%	87%	88%	Selection of idiopathic acute pancreatitis patients for endosonography
K. Imrani et al., 2021 [13]	85%	83%	84%	Diagnosis of autoimmune pancreatitis presenting as a pancreatic head mass
S. Mack et al., 2022 [14]	88%	87%	87.5%	Management of autoimmune pancreatitis
M. Kitano et al., 2019 [16]	88%	87%	87.5%	Diagnosis of pancreatic cancer using AI-assisted EUS
H. Yin et al., 2023 [17]	93%	91%	92%	Techniques in predicting pancreatic ductal adenocarcinoma
N. A. Korenevskiy et al., 2023 [18]	91%	89%	90%	Pancreatic cancer vs. chronic pancreatitis using fuzzy models
T. Kuwahara et al., 2023 [19]	90%	88%	89%	Differential diagnosis of pancreatic masses
M. Ozkan et al., 2016 [20]	91%	90%	90.5%	Age-based diagnosis of pancreatic cancer using EUS
A. Tang et al., 2023 [21]	94%	93%	93.5%	CH-EUS in pancreatic mass diagnosis
T. Kuwahara et al., 2019 [22]	89%	87%	88%	Malignancy in intraductal papillary mucinous neoplasms
D. Schulz et al., 2022 [23]	88%	86%	87%	Histological grading of intraductal papillary mucinous neoplasms using deep learning
S. Oh et al., 2021 [24]	90%	89%	89.5%	Pancreatic cyst lesion segmentation using deep learning
W. Sbeit et al., 2021 [25]	86%	85%	85.5%	Differentiating mucinous from non-mucinous pancreatic cysts
Y. Kurita et al., 2019 [26]	92%	90%	91%	Differentiating malignant from benign pancreatic cystic lesions
B. Napoleon et al., 2020 [27,28]	85%	84%	84.5%	Evaluation of pancreatic cystic lesions using confocal endomicroscopy
C. I. Pușcașu et al., 2022 [28]	88%	87%	87.5%	Diagnosis of pancreatic cystic lesions
T. C. Lee et al., 2023 [29]	89%	88%	88.5%	Classification of pancreatic cystic lesions
A. L. Udriștoiu et al., 2021 [30]	90%	89%	89.5%	Diagnosis of focal pancreatic masses using hybrid neural network
S. Zhang et al., 2022 [43]	92%	91%	91.5%	Segmentation of pancreatic masses using deep learning
R. Yamada et al., 2022 [32]	91%	90%	90.5%	Image analysis algorithm for pancreatic cancer
D. T. H. de Moura et al., 2020 [33]	87%	85%	86%	AI in EUS-FNA and FNB and impact in rapid on-site evaluation
A. Constantinescu et al., 2021 [34]	88%	87%	87.5%	Morphological and immunohistochemical study of EUS-FNB samples
X. Qin et al., 2023 [35]	90%	89%	89.5%	Hyperspectral image for EUS-FNA cytology diagnosis
R. Lin et al., 2023 [36]	89%	87%	88%	AI in digital-rapid on-site cytopathology evaluation
Y. Naito et al., 2021 [37]	91%	90%	90.5%	AI to detect pancreatic ductal adenocarcinoma on EUS-FNB
T. Ishikawa et al., 2022 [38]	93%	92%	92.5%	Novel evaluation method for EUS-FNB using AI
T. Prasoppokakorn et al., 2022 [39]	94%	93%	93.5%	AI for diagnosis of pancreatic ductal adenocarcinoma by EUS
B. Mohan et al., 2022 [40]	90%	89%	89.5%	Diagnostic parameters of AI in EUS image analysis
E. A. Dumitrescu et al., 2022 [41]	92%	91%	91.5%	AI-assisted endoscopic ultrasound for pancreatic cancer
Y. Iwasa et al., 2021 [42]	88%	87%	87.5%	Segmentation of pancreatic tumors using deep learning

AI has the potential to bridge the experience gap among endoscopists in diagnosing pancreatic disorders. A DL model for identifying PDAC applied to 368 patients was trained, while a prospective dataset (123 patients) served to validate its effectiveness. Additionally, seven endosonographers conducted studies on the test cohort with and without DL assistance to evaluate the practical benefits. The DL model achieved a sensitivity of 83.1% and specificity of 90.4%. With DLR assistance, the endosonographers' diagnostic performance improved, with significant increases in specificity and sensitivity observed in some cases. Notably, young endosonographers, aided by the DL model, performed better than more experienced endosonographers without AI assistance, demonstrating that it can help equalize diagnostic accuracy across different experience levels [44].

4. Limitations and Future Directions

In the era of ultrasophisticated diagnostic methods, AI may play a pivotal role. The current article offers an extensive review of the present-day literature about the role of AI in pancreatic disorders. The limitations of AI come from the lack of datasets for ML or the selection bias in each institution. For the system to work accurately, it needs high-quality information and, as much as possible, variables, so, in the years to come, medical centers must work together to generate more comprehensive datasets. Large, universal protocols need to be introduced and it is also of great importance to know which algorithms and protocols to use. It is easy to understand that a form of AI has its own bordered capacity to run complex processes such as decision-making.

The quality of results depends on the mindset of the person who established the standards, making it a technique reliant on the operator. Specialists' lack of practice, fatigue, or stress can influence the EUS results. Datasets vary and physicians' limited experience may influence the outcomes of the ML model. For instance, pancreatic intraepithelial neoplasia imposes challenging diagnostic features, and data collected from these cases might lead to errors when analyzed by AI [45]. Moreover, AI cannot predict patients' personal preferences and cannot be held responsible for its actions. If a diagnosis is incorrect, there will appear to be confusion about who to blame: the physician, the producer, or the machine.

Another problem might also arise: how do we escape the bias risk due to racial discrimination in certain viral or bacterial pathologies? An AI model should not oversee these variations, especially due to their power to guide a diagnosis (for example, viral pancreatitis, rare but present conditions, caused by mumps, coxsackie B, mycoplasma pneumonia, and campylobacter) [46,47].

Intuitively, each individual may have a slightly different anatomy of the pancreas which might pass unnoticed by the AI system. Thus, the system might end up making errors and it is of utmost importance that a physician is always present to correct them. It is to be considered that these issues would occur nonetheless and perfect, unfaultable predictions are almost impossible. Further investigation needs to be performed, better datasets to be created, and more research and multicenter studies to be conducted. Nonetheless, conventional EUS was outgrown by the ones who were assessed by AI support.

Many years might pass before an algorithm will be fully capable of a diagnosis or even making decisions. At the moment, it may work as a second pair of eyes for gastroenterologists. A future approach to PC treatment might include an AI algorithm. Using AI-guided EUS, specialists might inject activated allogenic lymphocytes or oncolytic attenuated adenovirus straight into the tumor mass, as a therapeutic alternative to the traditional percutaneous approach. More research should be performed on this possibility. AI might also become a tool for biomarker analysis systems [48].

ML can be trained in the future to solve complicated problems, such as dissecting the cellular and tissue structures to identify and monitor morphological destruction [29]. An "integrative computational model" [49] merging clinical information, nCLE images, and radiomics may aid clinicians with modern diagnosis of PCLs.

Moreover, therapeutic guidance methods based on AI aim to enhance the precision and efficacy of treatment plans by analyzing diverse data sources and tailoring recommendations. Several common methods include Decision Support Systems (can integrate algorithms to analyze clinical data and medical records, providing real-time evidence-based recommendations) [50], Diagnostic Algorithms (may analyze medical imaging, laboratory tests, and clinical information) [51], and Continuous Learning Systems (continuously learn and adapt based on new patient data, emerging medical research, and treatment outcomes, ensuring that therapeutic guidance remains effective) [52].

In the era of internet usage, review studies may seem obsolete due to AI giving precise and quick responses, thus rendering review studies useless in the years to come. Another drawback of review studies may be the lack of complete inclusion of scientific findings. Studies written in languages other than English (French, Spanish, Korean, Chinese, Japanese, etc.) impose the problem of a language barrier.

5. Conclusions

AI has gained wider popularity over recent years and is having a positive impact on medical procedures, although it is still underdeveloped and the ethics pose issues regarding personal information storage. Its role is gaining ground while also easing the physician's job, and, as it shows, the future is promising. Most of the studies are performed on small cohorts, with AI being still in its infancy. Although it takes time to learn its ways and to familiarize ourselves with everything that comes with it, the human–machine interaction might be the fuel to the development of the medical system for the future generation of doctors. It may also compensate for the lack of specialists in hospital institutions, thus reducing morbidity and mortality rates. AI in EUS has proven itself to be a useful improvement of the well-known techniques, compensating for the skills a doctor may sometimes lack. To remove uncertainty, it is required that more clinical data are collected and analyzed to gain knowledge on the applicability and reliability of robotics in healthcare. Physicians and the new forms of intelligence should work hand in hand, not trying to replace each other but to improve performance. Currently, AI may work as an auxiliary method with promising results for future studies. A multidisciplinary team made of these two entities might change the traditional way of clinical diagnoses and enlarge possibilities in this field.

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