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Artificial Intelligence in Pancreatic Imaging: A Systematic Review

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ABSTRACT

The rising incidence of pancreatic diseases, including acute and chronic pancreatitis and various pancreatic neoplasms, poses a significant global health challenge. Pancreatic ductal adenocarcinoma (PDAC) for example, has a high mortality rate due to late-stage diagnosis and its inaccessible location. Advances in imaging technologies, though improving diagnostic capabilities, still necessitate biopsy confirmation. Artificial intelligence, particularly machine learning and deep learning, has emerged as a revolutionary force in healthcare, enhancing diagnostic precision and personalizing treatment. This narrative review explores Artificial intelligence's role in pancreatic imaging, its technological advancements, clinical applications, and associated challenges. Following the PRISMA-DTA guidelines, a comprehensive search of databases including PubMed, Scopus, and Cochrane Library was conducted, focusing on Artificial intelligence, machine learning, deep learning, and radiomics in pancreatic imaging. Articles involving human subjects, written in English, and published up to March 31, 2024, were included. The review process involved title and abstract screening, followed by full-text review and refinement based on relevance and novelty. Recent Artificial intelligence advancements have shown promise in detecting and diagnosing pancreatic diseases. Deep learning techniques, particularly convolutional neural networks (CNNs), have been effective in detecting and segmenting pancreatic tissues as well as differentiating between benign and malignant lesions. Deep learning algorithms have also been used to predict survival time, recurrence risk, and therapy response in pancreatic cancer patients. Radiomics approaches, extracting quantitative features from imaging modalities such as CT, MRI, and endoscopic ultrasound, have enhanced the accuracy of these deep learning models. Despite the potential of Artificial intelligence in pancreatic imaging, challenges such as legal and ethical considerations, algorithm transparency, and data security remain. This review underscores the transformative potential of Artificial intelligence in enhancing the diagnosis and treatment of pancreatic diseases, ultimately aiming to improve patient outcomes and survival rates.

All authors contributed equally to the study.

1 | Introduction

The increasing incidence of pancreatic diseases poses a significant global health challenge. Recent studies have indicated a rising trend in the occurrence of acute and chronic pancreatitis over time, reflecting a growing burden on healthcare systems worldwide [1–3]. Pancreatic neoplasms, including solid tumors like pancreatic ductal adenocarcinoma (PDAC) and pancreatic neuroendocrine neoplasms (PNEN), along with various cystic lesions, are on a troubling rise [4]. Despite being the seventh among cancers globally, pancreatic cancer (PC) is one of the most lethal, with a high mortality rate closely mirroring its incidence [5, 6].

In this challenging context, artificial intelligence (AI), and especially deep learning (DL), has emerged as a powerful force in healthcare, offering new avenues for enhancing diagnostic precision and personalizing treatment. However, the integration of AI into healthcare also introduces challenges, including legal and ethical considerations, algorithm transparency and data security concerns [7]. This narrative review aims to provide a comprehensive overview of the role of AI in pancreatic imaging, touching on the technological advancements and clinical applications, but also challenges and limitations of a technology that is currently evolving rapidly.

2 | Materials and Methods

The present study followed the Preferred Reporting Items for Systematic Review and Meta-Analysis of Diagnostic Test Accuracy Studies (**PRISMA-DTA**) guidelines. A comprehensive search has been performed in medical databases such as PubMed, Scopus and Cochrane Library, focusing on articles relevant to the application of AI, ML, DL, and radiomics in pancreatic imaging. The following MeSH (Medical Subject Headings) terms and keywords were used: "Artificial Intelligence," "Machine Learning," "Deep Learning," "Neural Networks," as well as "Pancreas," "Pancreatitis," "Pancreatitis, Acute Necrotizing," "Pancreatitis, Chronic," "Pancreatic Neoplasms/Diagnostic Imaging," "Ultrasonography," "Tomography, X-Ray Computed," "Magnetic Resonance Imaging," "Positron Emission Tomography," "Endoscopic Ultrasound." Specific search strings were constructed for each library to ensure thorough retrieval. In the initial stages of the systematic literature review, we utilized advanced AI-based tools including ChatGPT 4o, Perplexity AI, and Microsoft Co-Pilot to assist in developing search queries and identifying relevant keywords and synonyms, including MeSH terms (Supporting Information S1).

We included in the analysis original research articles involving human subjects, written in English and published (or available as "online first"), up until March 31, 2024. After initial retrieval, duplicates were screened and assessed for eligibility based on their relevance to AI and pancreatic imaging. This phase involved a careful review of titles and abstracts, followed by full-text screening of selected articles. The detailed process of study inclusion can be summarized in the following flow diagram based on the PRISMA methodology (Figure 1). Thus, an initial search in three databases yielded 1069 studies, with 446 studies screened after removal of duplicates. After the initial exclusion of 256 studies, 190 were retrieved and 95 were excluded after retrieval, with a total number of 95 studies included in the review.

3 | Technological Advancements

Recent technological advancements in AI models and algorithms tailored for pancreatic imaging have shown significant promise in enhancing the detection and diagnosis of pancreatic diseases [8], particularly PC [9]. Thus, AI techniques usually consist in the integration of DL classifiers and radiomics feature extraction applied for imaging modalities like multi-slice CT scans, MR images, and endoscopic ultrasound (EUS), providing precise segmentation of pancreatic tissues and aiding in the differentiation between benign and malignant lesions [8–10]. Moreover, AI-driven algorithms have been utilized to predict survival time, recurrence risk, metastasis development, and therapy response in PC patients.

Radiomics approaches for processing CT/MR/EUS images have shown promising results by systematically extracting quantitative features from images (manually crafted features) and identifying subtle changes indicative of pathology, although they are often regarded as a pre-DL method [8]. Most of the recent AI-driven DL methods are utilizing convolutional neural networks (CNNs) to enable accurate image segmentation, contour identification, and disease classification (Figure 2) [11]. Several DL techniques have been used extensively in the pancreas imaging literature, most of them based on CNNs (Supporting Information S2) [12–14].

4 | Detection and Segmentation

Early qualitative studies have shown that DL has the potential to greatly improve the detection and segmentation of pancreatic lesions in imaging studies [15–17]. Nevertheless, automated segmentation of the pancreas remains insufficiently accurate due to several reasons: (1) there are different shapes and sizes of the pancreas; (2) the pancreatic tissue is soft and highly deformable so it can be compressed or moved by its surrounding organs; and (3) the margins of the pancreas are often indistinguishable from that of the intestine, vessels, abdominal fat and other neighboring soft tissues, generating a significant amount of uncertainties along the boundaries of pancreatic and non-pancreatic tissues. Given all the above-listed reasons, the accurate detection of pancreatic margins is still insufficiently achieved in clinical practice [18]. Most of the studies report metrics like the Dice-Sørensen coefficient (DSC), which represents a statistical measure that evaluates the similarity between two sets, commonly used to assess the accuracy of image segmentation in medical imaging, ranging from 0 (no overlap) to 1 (perfect overlap) (Figure 3). The studies reporting the usage of various DL approaches for accurate detection and segmentation of CT/MR/EUS images are presented in Table 1.

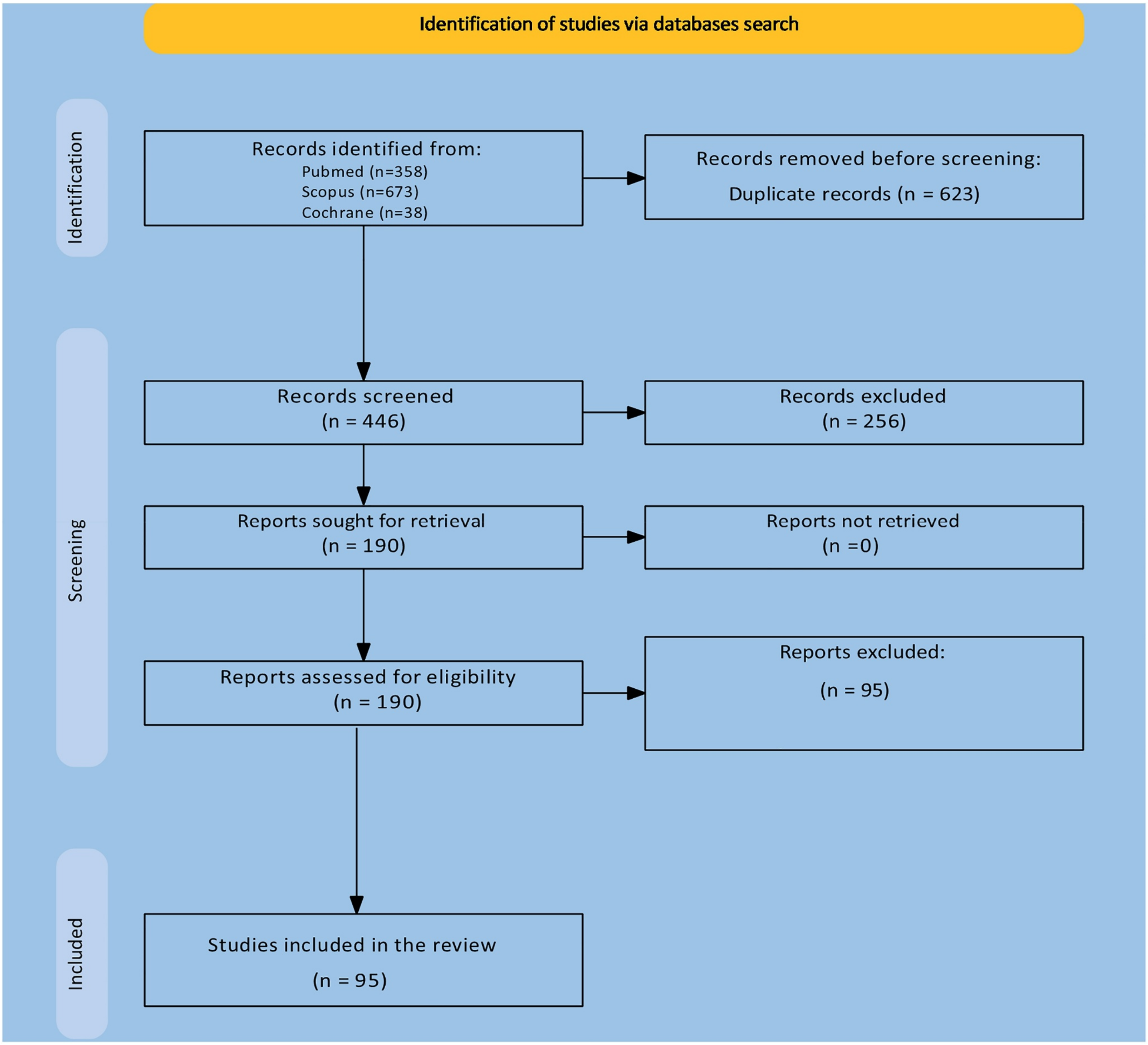

FIGURE 1 | The process of study inclusion based on PRISMA methodology.

4.1 | Computer Tomography

CT imaging, especially with a pancreatic protocol, offers valuable information regarding the size, extent, and local invasion of tumors. However, detecting small or subtle pancreatic lesions, especially at an early stage, remains a significant challenge. Several DL models enhance the early diagnostic process by pinpointing tumors that may not yet be symptomatic or visible on routine CT scans. Such advancements in detection could shift clinical practices toward earlier, more proactive treatment strategies, thereby improving prognosis for patients with PC.

Segmentation of the pancreas and pancreatic tumors is an area where AI has demonstrated significant potential. Accurate segmentation is vital for diagnosis, treatment planning, and follow-up, particularly in determining tumor boundaries and vascular involvement. The pancreas is surrounded by numerous other soft tissues, and its shape and size can differ significantly between patients, which complicates segmentation efforts. Nevertheless, various DL models have been tested with different training and testing strategies, as well as variable success for segmentation, usually yielding DSCs of 0.6–0.96 [14, 19–39].

Hierarchical DL models achieved acceptable DSC values for pancreatic segmentation on CT, marking a significant improvement over earlier methods [19–21]. Other studies also used complex architectures for segmentation although they did not use hierarchical models in the same structured way [22, 23]. Cascade networks, which involve multiple stages where the output of one network becomes the input to another, are often considered hierarchical because they process data in stages and refine results progressively [24, 25].

Several groups used variations of the U-Net architecture to improve the accuracy and robustness as well as the speed of segmentation as compared to medical experts. A hierarchical

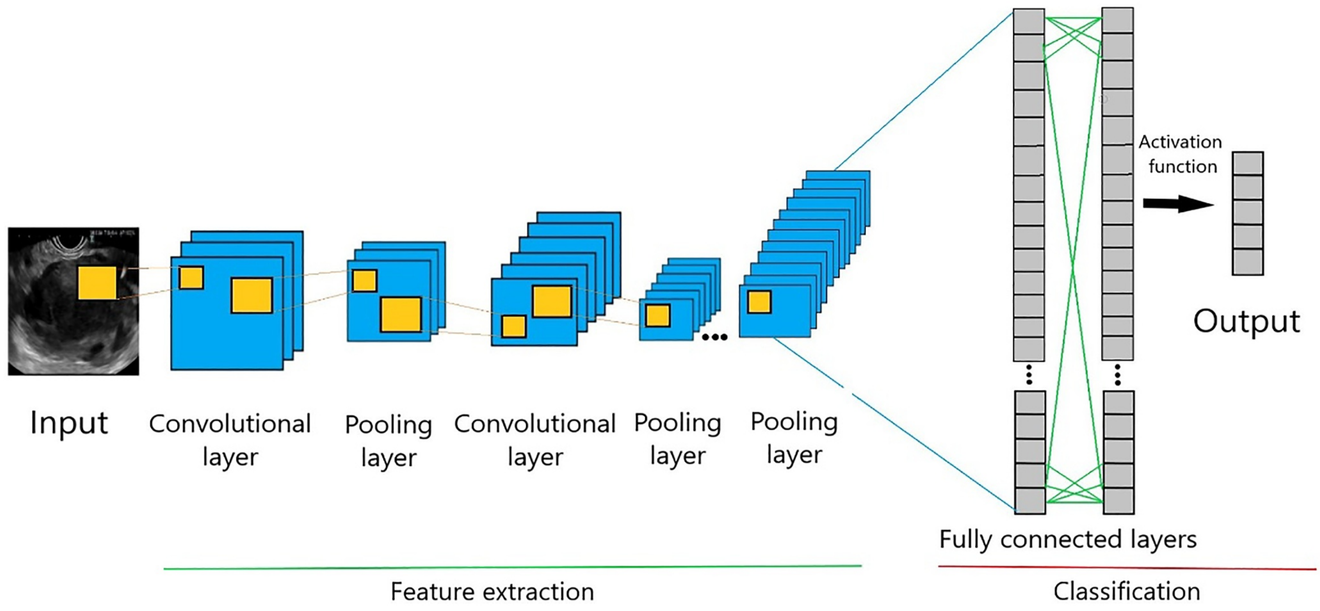

FIGURE 2 | A schematic drawing showing how a CNN model is analyzing pancreatic imaging data.

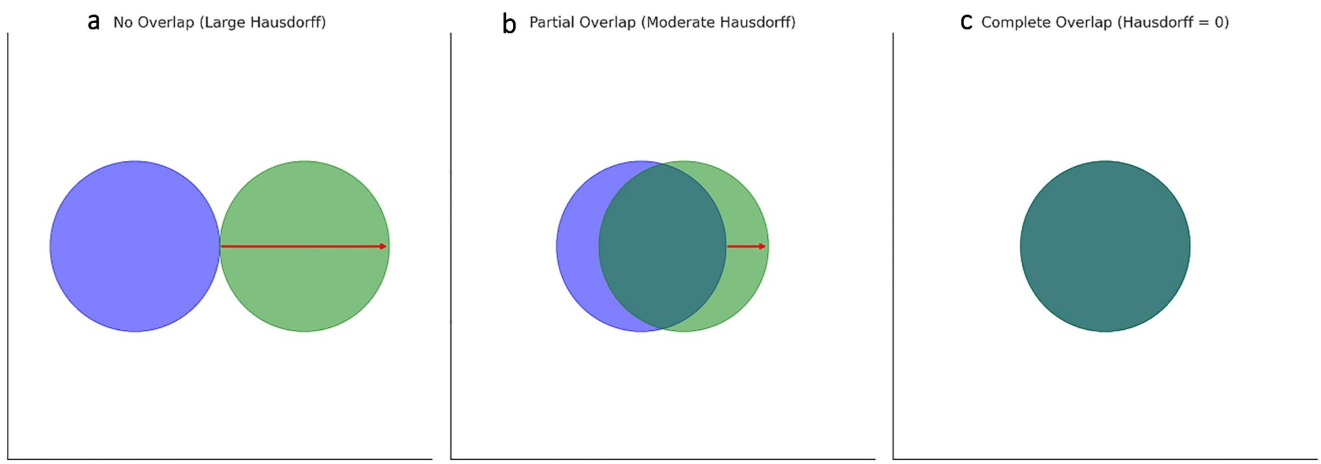

FIGURE 3 | Situations representing different DICE scores: (a) No Overlap (DICE = 0) > the two areas do not overlap at all; (b) Partial Overlap (DICE < 1) > the circles overlap to some extent, leading to a DICE score between 0 and 1; (c) Complete Overlap (DICE = 1) > The circles perfectly overlap, resulting in a maximum DICE score of 1. The Hausdorff distance that indicates the maximum distance between the two sets as measured from their boundaries is also represented (red arrow).

approach using a reinforcement learning strategy for localization and a deformable U-Net for segmentation was used to refine the segmentation progressively [27]. Similar approaches compared manual segmentation to CNN-based volumetric segmentation, focusing on accuracy and efficiency, while they showed that expert manual segmentation can be reached by DL models with a significant reduction of the time required for segmentation [28, 29]. Other DL models include MAD-UNet, which integrates a U-shaped network architecture boosted with an attention mechanism to better capture the complex features of pancreatic tissues [30]. Another DL approach for automated pancreas segmentation in CT scans has been introduced by Panda et al. [31]. This two-stage model utilizes 3D CNNs based on a modified U-net architecture to achieve accurate volumetric segmentation with the ground truth represented by the curated images from two radiologists who excluded pancreatic disease CT images from the initial dataset. Key results from the study include a DSC of 0.91 on the test set and no significant difference between model-predicted and ground truth (GT) pancreatic volumes. On an external dataset, the model maintained high reliability, outperforming human readers at both full and reduced radiation doses, with a mean DSC of 0.96 at reduced dose CT scans. Addition of a graph enhancement module or deformable convolution modules on top of U-Net architectures seems to better capture spatial relationships [32, 33].

Furthermore, DL-based automatic semantic segmentation techniques have been clinically tested in a large dataset of 1006 healthy patients, using four 3D segmentation networks (all based on U-NET architecture: Basic U-Net, Dense U-net, Residual U-net and Residual Dense U-net), achieving a high accuracy and effectiveness, with a DSC of over 0.8 [34]. Likewise, a tunicate-

TABLE 1 | Studies report the usage of various DL approaches for accurate detection and segmentation of CT/MR/EUS images.

First author [Ref]	Imaging	Type of AI	Application of AI	Image datasets	Accuracy data
Fu et al. [19]	CT	Hierarchical deep learning framework	Pancreas segmentation	Local hospital dataset	DSC: 0.76
Roth et al. [20]	CT	Holistically-nested convolutional networks (HNNs)	Pancreas segmentation	NIH dataset	DSC: 0.81
Chen et al. [21]	CT	Multi-scale feature fusion model	Pancreas segmentation	NIH dataset	DSC: 0.87
Hu et al. [22]	CT	DenseASPP network	Pancreas segmentation	NIH dataset and local hospital dataset	DSC: 0.85
Zhao et al. [23]	CT	Knowledge-aided CNN	Pancreas segmentation	VISCERAL challenge dataset (20 non-contrast CT and 20 contrast-enhanced CT volumes)	DSC: 0.82
Yang et al. [24]	CT	Cascade neural network	Pancreas segmentation	NIH dataset	DSC: 0.87
Zhang et al. [25]	CT	Multi-atlas registration, 3D level-set, coarse-to-fine-to-refine segmentation	Pancreas segmentation	Three different datasets with 399 CT volume images	DSC: 0.82
Kawamoto et al. [26]	CT	Residual deep supervision network	Pancreas segmentation	91 CTs (42 normal, 49 abnormal)	DSC: 0.87 (normal), 0.85 (abnormal)
Man et al. [27]	CT	Deep Q learning, geometry-aware U-net	Pancreas segmentation	NIH dataset	DSC: 0.84
Boers et al. [28]	CT	Interactive 3D U-net (iUnet)	Pancreas segmentation	The cancer Image archive (TCIA) pancreas-CT dataset and the beyond the cranial vault (BTCV) Abdomen dataset for training and Radboud UMC local dataset	DSC: 0.78 (auto), 0.86 (interactive)
Khasawneh et al. [29]	CT	CNN-based approach	Pancreas segmentation	294 portal venous CT scans	DSC: 0.88
Li et al. [30]	CT	MAD-UNet	Pancreas segmentation	NIH dataset and MICCAI segmentation decathlon challenge dataset	DSC: 0.86
Panda et al. [31]	CT	3D CNNs, modified U-net	Pancreas segmentation	TCIA and NIH dataset	DSC: 0.91 (TCIA) and 0.89 (NIH)
Liu et al. [32]	CT	GEPS-net	Pancreas segmentation	NIH dataset four-fold cross-validation	DSC: 0.84
Huang et al. [33]	CT	Deformable U-Net	Pancreas segmentation	NIH dataset	DSC: 0.87
Lim et al. [34]	CT	Deep neural network: Basic U-net, residual U-net, dense U-net, residual dense U-net	Pancreas segmentation	1006 healthy patients	DSC: 0.84
Gandikota et al. [35]	CT	Tunicate-swarm algorithm, deep echo state network (W-NET)	Pancreatic cancer segmentation and classification	Benchmark dataset with 500 samples	Sensitivity, specificity and accuracy > 99%

(Continues)

TABLE 1 | (Continued)

First author [Ref]	Imaging	Type of AI	Application of AI	Image datasets	Accuracy data
Dogan et al. [14]	CT	Mask R-CNN, 3D U-net	Pancreas segmentation	NIH dataset	DSC: 0.86
Mahmoudi et al. [36]	CT	Deep convolutional neural networks (modified U-Net > TAU-Net)	PDAC and vessel segmentation	MICCAI segmentation decathlon challenge dataset and local dataset	DSC: 0.6
Wang et al. [37]	CT/PET	Multi-modal fusion and calibration networks (MFCNet)	Pancreas segmentation	Public dataset (head and neck cancer), in-house dataset (pancreas cancer)	DSC: 0.76
Liu et al. [38]	CT	3D self-attention U-net	Multiple organ segmentation to identify organs-at-risk during pancreatic cancer radiotherapy	Local dataset with CT images from 100 pancreatic cancer patients undergoing pancreatic radiotherapy	DSC: 0.86–0.96 for different organs
Dai et al. [39]	CBCT	CycleGAN, MS R-CNN	Multiple organ segmentation for delineation of organs-at-risk during pancreatic cancer radiotherapy	Two separate datasets. First, CT and CBCT images from 35 pancreatic cancer patients. Second, 120 sets of CBCT images with corresponding ground-truth for contours from 40 pancreatic cancer patients	Mean DSC 0.92
Cai et al. [40]	MR	Graph-based decision fusion, CNN	Pancreas segmentation	78 MRI scans	DSC: 0.76
Chen et al. [41]	MR	2D U-net, densely connected networks	Multi-organ segmentation	Multi-slice MRI scans from 102 subjects	DSC: 0.87–0.96 (varies by organ)
Zhang et al. [42]	MR	Prior knowledge-guided deep learning	Complex anatomy segmentation	T2-weighted MRI images from 75 patients	DSC: 0.87 (pancreas)
Bongratz et al. [43]	CT/MR	Deep diffeomorphic mesh deformations (UNetFlow)	Abdominal organ segmentation	1000 abdominal CT and 70 MRI scans	DSC: 0.95 (liver), 0.91 (kidney), 0.92 (spleen), 0.72 (pancreas)
Kart et al. [44]	MR	nnU-net	Abdominal organ segmentation	UK Biobank (UKBB) and German National Cohort (GNC)	DSC: > 0.9 (liver, spleen, kidneys), 0.82 (UKBB) and 0.89 (GNC) (pancreas)
Rickmann et al. [45]	MR	Deep neural network (QuickNAT and U-Net)	Abdominal organ segmentation	German National Cohort, UK Biobank, Kohorte im Raum Augsburg	DSC: > 0.9 (liver, spleen, kidneys), 0.74 (pancreas)
Mazor et al. [46]	MR	MC3DU-net	Pancreatic cyst segmentation	158 MRI studies comprising 840 cysts	DSC: 0.80
Liang et al. [47]	MR	Square-window based CNN	Pancreatic tumor segmentation	Approximately 475,000 image patches	DSC: 0.73
Zhang et al. [48]	EUS	Deep-learning based approach	Pancreas segmentation and station recognition	19,486 EUS images for station classification, 2207 EUS images for pancreas segmentation	DSC: 0.836 (internal segmentation) DSC: 0.715 (external segmentation)

swarm algorithm with DL based pancreatic cancer segmentation and classification used a W-net segmentation approach to define the affected region on CT [35]. The performance of the proposed model was tested on a benchmark dataset with 500 samples comprising PC and non-pancreatic tumor, outperforming other systems with accuracy, sensitivity, and specificity over 99%.

As mentioned, two-step (cascade) methods seem to be more beneficial. This approach usually involves two phases: for example, Mask R-CNN for rough pancreatic localization on 2D CT slices and 3D U-Net for refined segmentation [14]. Additional segmentation of surrounding vessels, beside PDAC, can be performed by 2D Attention U-Net and Texture Attention U-Net (TAU-Net), followed by a 3D-CNN ensemble model used to achieve precise segmentation through multiple fine-tuning steps [36].

Significant improvements in segmentation accuracy based on three-dimensional PET-CT images have also been reported previously [37].

Segmenting multiple organs in CT images has also been developed with a specific focus on improving the accuracy of pancreatic segmentation for radiotherapy planning [38]. The proposed method employs a 3D Self-attention U-Net network, leveraging attention mechanisms to enhance the model's ability to focus on relevant features in the images. The contours generated using the proposed method closely resemble the ground-truth manual contours, with a high DSC of 0.9. A similar approach assessed a DL-based method for segmenting multiple organs in cone-beam computed tomography (CBCT) images to aid adaptive radiotherapy for PDAC [39]. The study achieved significant improvements in segmentation performance, with a DSC reaching up to 0.91 for certain organs, demonstrating its effectiveness in clinical settings for better treatment planning and delivery.

4.2 | Magnetic Resonance

Initial studies reporting accurate segmentation of the pancreas in MR scans integrated CNNs for tissue detection with graph-based decision fusion to enhance segmentation accuracy, and obtained a DSC of 0.76 [40]. Automated DL-based Abdominal Multi-Organ segmentation (ALAMO) has been developed for automatic segmentation of multiple abdominal organs-at-risk [41], based on a 2D U-net combined with densely connected networks and tailored data augmentation strategies. This approach achieved an impressive performance, with high DSCs in the range of 0.87–0.96 for nine organs, completing a full 3D volume within 1 min. A generalized rather than organ-specific DL semiautomatic segmentation model using a 2D U-Net DL model to guide auto-for the next slide also seems to be beneficial, yielding a DSC of 0.87 for the pancreas and higher values for other organs [42]. Likewise, a novel U-Net-Flow approach for segmenting four abdominal organs in CT and MRI scan achieved a DSC of 0.95 for liver segmentation, 0.91 for kidney segmentation, 0.72 for pancreas and 0.92 for spleen segmentation [43].

Automated whole-body MRI segmentation has been tested on images from the UK Biobank (UKBB) and German National Cohort (GNC), using nnU-net for training using 400 T1-weighted MR image datasets from healthy volunteers and achieved a mean DSC for the liver, spleen, and kidneys above 0.9, while for the pancreas, the DSC was around 0.82 for UKBB and 0.89 for GNC data [44]. AbdomenNet, another DL model designed to realize automatic segmentation of abdominal organs in MRI scans, has been developed to overcome the challenge of time-consuming manual segmentation, yielding a DSC of 0.95 for liver segmentation, 0.91 for spleen segmentation, and 0.74 for pancreas segmentation [45].

The first DL model designed to automatically detect and segment pancreatic cysts in MRI studies during follow-up employs a multisequence approach to enhance segmentation accuracy [46]. More precisely, this cascaded pipeline method includes a first step with segmentation of the pancreas based on a region of interest in the TSE MRI scan, which is transferred in a second step to the MRCP scan where 3D U-Nets perform the segmentation and identification of pancreatic cysts, thus achieving a mean DSC of 0.80 for cysts larger than 5 mm in diameter.

A retrospective study including a small number of patients tested a model used for the automatic segmentation of pancreatic tumors in multi-parametric MRI to rapidly generate the gross tumor volume (GTV) for radiation therapy, using a square-window based CNN architecture, thus yielding significant accuracy and a high DSC of 0.82 [47].

4.3 | Endoscopic Ultrasound

While EUS has been proven to be an invaluable procedure in many clinical scenarios, there is a significantly steep learning curve with this procedure, which can take years to become proficient. An illustrative example of how AI cand help in EUS training and quality control is a DL-based system named BP MASTER [48]. The system demonstrated 90% accuracy in station classification and segmentation, performing comparably to expert endoscopists, with a DSC of 0.77 and 0.81 in blood vessel and pancreas segmentation.

5 | Clinical Applications

AI applications for pancreatic lesions in a clinical setting have primarily focused on lesion detection, segmentation, characterization and monitoring (Figure 4). The studies reporting the usage of various DL approaches for CT/MR/EUS used for diagnosis of pancreatic lesions are presented in Table 2. Moreover, AI prognostic abilities have been extensively challenged in various scenarios using different imaging techniques, as summarized in Table 3.

5.1 | Computer Tomography

Abdominal CT scan with the pancreatic protocol is widely utilized as a pivotal method for diagnosing and determining the stage of pancreatic tumors. It enables accurate assessment of tumor size, vascular involvement, and the extent of disease

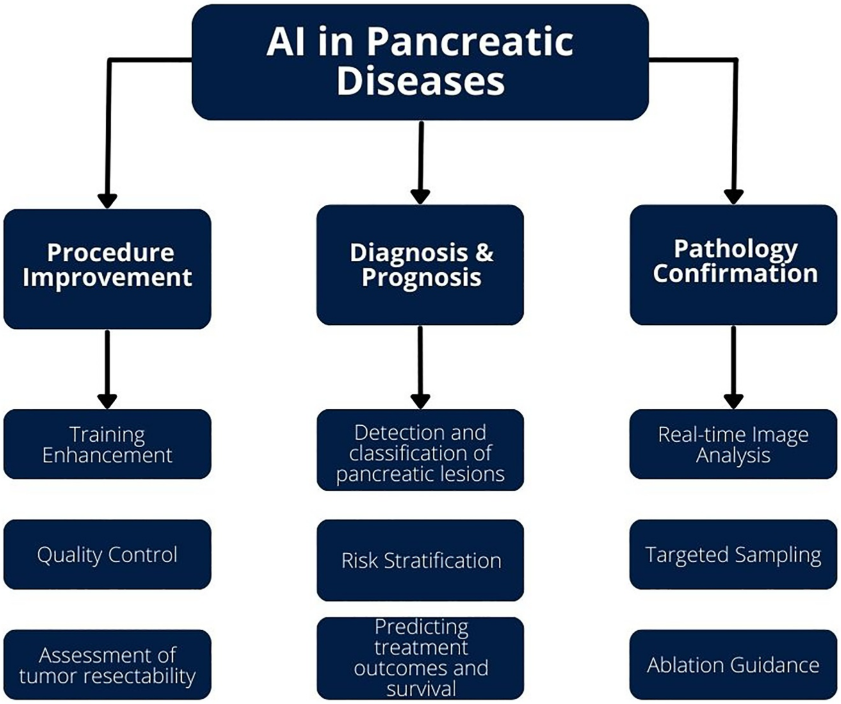

FIGURE 4 | AI clinical applications for pancreatic diseases.

spread [49, 111]. AI has been further applied to CT imaging to improve the detection and characterization of pancreatic lesions for risk stratification and prediction of treatment response.

Multiple studies have demonstrated significant promise for the use of AI to identify PDAC at an early stage using CT scans [49–53]. Identification of PDAC in the pre-diagnostic phase is of utmost importance and a radiomics-based AI algorithm tackling this challenge has been proposed by Mukherjee et al. This model showed a high AUC in diagnosing PDAC within 3–36 months before clinical diagnosis, surpassing the performance of two radiologists who individually assessed the images in the test set [52]. Detecting pre-invasive cancer using CT scans and a 3D CNN was shown to be feasible and highly accurate in another study by Korfiatis et al. [49]. Their model was able to detect PDAC a median of 475 days (range, 93–1082 days) before the clinical diagnosis. Imaging techniques like CT or MR are known for their limited accuracy in detecting small pancreatic lesions defined by their diameter below 15–20 mm. Nevertheless, one recent algorithm [50] was able to differentiate between PDAC and a healthy pancreas using portal venous CT scans, effectively detecting pancreatic cancer on CT scans and exhibiting satisfactory sensitivity for tumors measuring less than 2 cm. Another study contributing to the field is Park et al., who developed a DL algorithm to distinguish between images of pancreatic neoplasms (such as PDAC, neuroendocrine neoplasm, solid pseudopapillary neoplasm, intraductal pancreatic mucinous neoplasm, serous cystic neoplasm, and mucinous cystic neoplasm) and images without any pancreatic abnormalities [53].

Moving further to differential diagnosis, Anai et al. [54] developed a support vector machine (SVM) classifier using CT texture-based analysis to distinguish between focal-type autoimmune pancreatitis (AIP) and PDAC. Moreover, Ren et al. used CT and radiomics and evaluated their predictive capacity in distinguishing between pancreatic adenosquamous carcinoma (PASC) and PDAC [55]. The model demonstrated favorable outcomes as a noninvasive technique in distinguishing between PASC and PDAC, achieving an accuracy of 94.5%, sensitivity of 98.3%, specificity of 90.1%, positive predictive value (PPV) of 91.9%, and negative predictive value of 97.8%. Although the accuracy was impressive, there was a random division into training and testing datasets, based on a 10 times cross-validation analysis, with no external validation.

After the initial reports based on radiomics, an excellent approach was published by Cao et al., that used a cascade of three network stages that increase in model complexity [56]. Stage 1 involves pancreas localization using an nnU-Net model, with Stage 2 multi-task CNN used for lesion detection and pancreas segmentation, while Stage 3 is another multi-task CNN for the differential diagnosis, integrated with an auxiliary memory transformer branch to automatically encode the feature prototypes of the pancreatic lesions, such as local texture, position and pancreas shape, for more accurate fine-grained classification. PANDA, a deep learning tool trained on 3208 patients, achieved high accuracy in detecting pancreatic lesions in non-contrast CT (AUC 0.986–0.996) in a retrospective multicenter validation involving 6239 patients across 10 centers. Furthermore, it outperformed radiologists in sensitivity and specificity (92.9% and 99.9% respectively), and shows non-inferiority to contrast-enhanced CT in differentiating pancreatic lesion subtypes, making it promising for large-scale PDAC screening.

To date, surgical intervention remains the best treatment option for achieving potential long-term survival in PDAC. However, it is applicable to only a minority (10%–15%) of patients. The main factor in determining eligibility for tumor resection is the

TABLE 2 | Summary of studies reporting on CT/MRI/EUS based AI applications for the diagnosis of pancreatic lesions.

First author [Ref]	Imaging	Type of AI	Lesion type	Image datasets	Accuracy
Korfiatis et al. [49]	CT	3D CNN model	PDAC	Trained on 696 CT scans with PDAC, 1080 control CT with nonneoplastic pancreas. Evaluated on several multi-institutional datasets	Accuracy: 84% Sensitivity: 75% Specificity: 90% to detect occult PDAC at a median 475 days before diagnosis
Chen et al. [50]	CT	CNN	PDAC	546 patients with PDAC, 733 controls. Evaluated on a real-world multi-institutional dataset	Sensitivity: 89.7% Specificity: 92.8% for malignancy vs. control Sensitivity: 74.7% for tumors < 2 cm
Qureshi et al. [51]	CT	Radiomics	PDAC	108 CT scans	Accuracy: 86%
Mukherjee et al. [52]	CT	Radiomics	PDAC	Prediagnostic CT scans of 155 PDAC patients, 265 controls	Sensitivity: 95.5% Specificity: 90.3% Accuracy: 92.2% AUC: 0.98 (95% CI 0.94–0.98)
Park et al. [53]	CT	DL (nnU-Net)	Solid and cystic pancreatic lesions	852 patients in the training set, 603 in test set 1, 589 patients in test set 2	Sensitivity: 98%–100% for solid lesions, 92%–93% for cystic lesions ≥ 1.0 cm
Anai et al. [54]	CT	SVM	PDAC vs. AIP differential diagnosis	50 patients (20 with PDAC, 30 with AIP)	AUC = 0.920 in differentiating focal AIP from PDAC
Ren et al. [55]	CT	Radiomics	PDAC vs. PASC differential diagnosis	81 patients with PDAC, 31 patients with PASC	Accuracy: 94.5%, Sensitivity: 98.3%, Specificity: 90.1%
Cao et al. [56]	CT	PANDA model (stepwise training using nnU-net, CNNs and auxiliary transformer memory branch)	Lesion detection (normal vs. abnormal pancreas), primary diagnosis (PDAC vs. non-PDAC vs. normal), classification (PDAC or 7 subtypes of non-PDAC lesions)	Five patient cohorts: Internal development, internal test, external multicenter test, chest-CT test, and rel-world clinical evaluation cohort	AUC of 0.986–0.996, for lesion detection, sensitivity of 92.9% and specificity of 99.9%,
Yimamu et al. [57]	CT	Human-machine fusion ML model	PDAC resectability prediction	349 patients from 4 centers	AUC 0.884, Accuracy 82.5%, Sensitivity 84.2%, Specificity 82%
Bereska et al. [58]	CT	CNN	PDAC	Training set: 613 CT scans from 467 patients with pancreatic tumors, 50 controls Test set: 60 CT scans, 20 resectable, 20 borderline resectable, and 20 locally advanced tumors	80% agreement with the radiologist in classifying resectability
Miao et al. [59]	CT	DL	PDAC	509 PDAC patients	AUC 0.849, Sensitivity: 87.5%, Specificity: 72.8% for T4-PDAC

(Continues)

First author [Ref]	Imaging	Type of AI	Lesion type	Image datasets	Accuracy
Yao et al. [60]	CT	ResNet3D with contrast enhanced convolutional long short-term memory network	PDAC	Dataset A: 296 patients with PDAC; Dataset B1: 571 patients with PDAC; Dataset B2: 61 patients with IPMN; Dataset C: 281 patients with annotated pancreatic tumors public dataset provided by Memorial Sloan Kettering; Dataset D: combination of two public datasets of CT scans from 90 patients	*c*-index = 0.659 for survival prediction
Healy et al. [61]	CT	Radiomics	PDAC	Training cohort: 352 patients (5 Canadian centers) Validation cohort: 215 patients (34 Ireland centers)	*c*-index = 0.545, 95%: 0.543–0.546 for predicting OS/DFS
He et al. [62]	CT	Radiomics	NF-pNET vs. PDAC differential diagnosis	147 patients (80 PDAC, 67 atypical NF-pNET)	AUC 0.884
Li et al. [63]	CT	Volumetric CT texture analysis	Atypical pNET (hypovascular) vs. PDAC differential diagnosis	127 patients (50 PDAC, 77 pNET with 25 atypical pET)	AUC 0.887, Sn 90%, Sp 80%
Yu et al. [64]	CT	Texture analysis	Nonhypervascular pNEN vs. PDAC differential diagnosis	120 patients (40 PNEN, 80 PDAC)	AUC 0.929
Canellas et al. [65]	CT	Texture analysis	pNET	101 PNETs	Accuracy: 79.3% for predicting tumor grading
Gu et al. [66]	CT	Radiomics	pNET	138 PNETs (104 training cohort, 34 validation cohort)	AUC 0.902 (95% CI 0.798–1.000) for predicting tumor grading
Yang et al. [67]	CT	Radiomics	Pancreatic cystic lesions	53 SCA, 25 MCA	AUC 0.66 for 2 mm slice thickness, 0.75 for 5 mm slice thickness to differentiate SCA from MCA
Yang et al. [68]	CT	Texture analysis	Pancreatic cystic lesions	59 SCA, 32 MCA	AUC 0.893 for differentiating SCA from MCA
Shen et al. [69]	CT	ML algorithms—SVM, RF, ANN	Pancreatic cystic lesions	164 patients including 76 with SCA, 40 with MCN and 48 with IPMN	SVM Accuracy: 71.43% RF Accuracy: 79.59% ANN Accuracy: 71.43%
Hanania et al. [70]	CT	Quantitative imaging analysis	Pancreatic cystic lesions	53 IPMN (34 "high-grade," 19 "low-grade")	AUC 0.96 Sensitivity: 97% Specificity: 88%
Chen et al. [71]	CT	Radiomics	Acute pancreatitis	389 AP patients (271 primary cohort, 188 validation set)	AUC 0.941 for the primary set, 0.929 for the validation set

(Continues)

TABLE 2 | (Continued)

First author [Ref]	Imaging	Type of AI	Lesion type	Image datasets	Accuracy
Mashayekhi et al. [72]	CT	Radiomics	Recurrent acute pancreatitis (RAP), Chronic pancreatitis (ChP)	56 patient (20 RAP, 19 functional abdominal pain, 17 ChP)	Accuracy: 82.1%
Guo et al. [73]	MR	Radiomics	pNET	77 patients, MRI images	AUC: 0.813–0.989 for grade prediction
Song et al. [74]	MR	Radiomics	Hypovascular NF-pNET vs. SPN differential diagnosis	79 patients (57 SPN and 22 NF-pNET), MRI images	AUC: 0.92078
Jeon et al. [75]	MR	Texture analysis	Pancreatic cystic lesions	MRI scans of 248 patients with IPMN (106 malignant)	Diagnostic performance for predicting malignant IPMN 0.85 (95% CI, 0.80–0.89)
Cui et al. [76]	MR	Radiomic nomogram	IPMNs	Training cohort ($n = 103$ patients) Validation cohort 1 ($n = 48$) Validation cohort 2 ($n = 51$)	AUC for predicting high-grade BD-IPMN 0.880 (mean for 2 external validation cohorts)
Lin et al. [77]	MR	Radiomics	Acute pancreatitis	Training cohort (99 non-severe, 81 severe) Validation cohort (43 non-severe, 36 severe)	AUC: 0.848
Frokjaer et al. [78]	MR	Texture analysis	Chronic pancreatitis (ChP)	MRI scans of 77 patients with ChP and 22 healthy controls	Sensitivity: 97% Specificity: 100% Accuracy: 98%
Gu et al. [79]	EUS	Radiomics	PDAC	Training cohort (368 patients) Test cohort (123 patients)	AUC 0.936, Accuracy 86.3%, Sensitivity 83.1%, Specificity 90.4%
Kuwahara et al. [80]	EUS	EfficientNet	Solid pancreas masses, incl. PDAC	933 patients, 22,000 images	AUC 0.90 Sensitivity 96%
Tonozuka et al. [81]	EUS	Custom based CNN model + pseudo-colored feature mapping	PDAC	139 patients, 920 images used for training and validation	AUC 0.94, Sensitivity 92%, Specificity 84%
Udriştoiu et al. [82]	EUS	Custom based CNN model + long short-term memory network	PDAC	65 patients, 1300 collected images	AUC 0.97, Sensitivity 98.1%, Specificity 96.7%
Marya et al. [83]	EUS	CNN	AIP, PDAC	583 patients	Sensitivity 90% Specificity 93%
Tang et al. [84]	EUS	CNN	Solid pancreas masses	CH-EUS videos	Accuracy 88.9% for identifying malignancy

(Continues)

TABLE 2 | (Continued)

First author [Ref]	Imaging	Type of AI	Lesion type	Image datasets	Accuracy
Mo et al. [85]	EUS	Ultrasomics nomogram	PDAC vs. pNET differential diagnosis	231 patients, 127 with PDAC and 104 with pNET	AUC 0.884
Vilas-Boas et al. [86]	EUS	CNN	Mucinous versus non-mucinous PCL	5505 images from 28 PCLs (3725 mucinous and 1780 non-mucinous)	Accuracy 98.5% Sensitivity 98.3% Specificity 98.9%
Kuwahara et al. [87]	EUS	ResNet	IPMN	3970 EUS images	Sensitivity 95.7% Specificity 92.6% Accuracy 94.0%

imaging assessment of tumor-vascular contact. AI's ability to contribute to the field has also been tested. Several authors have developed ML models in this setting with good accuracy for the evaluation of the tumor vascular involvement and NCCN guidelines-based resectability [57, 58]. The TNM classification by the American Joint Committee on Cancer (AJCC) is the primary method used for staging PDAC [111]. Miao et al. [59] developed and validated an automated AI system that can accurately predict the T4 stage of PDAC using contrast-enhanced CT imaging. The model's performance was found to be similar to that of two skilled abdominal radiologists, with AUC values of 0.849, 0.834, and 0.857, respectively.

Survival prediction of patients with PDAC represents another challenge for AI proposed by several authors. Integrating radiomics and DL features extracted from CT scans has been shown to be superior to traditional Cox proportional hazard methods for survival prediction [88, 89]. More advanced models with self-learning capabilities are even able to predict resection margins preoperatively [60]. FDG-PET/CT radiomic features integrated into ML models are similarly capable of predicting survival in PDAC patients [90]. Prediction of tumor response to neoadjuvant therapy using AI is also challenging. Healy et al. [61] conducted a multicenter study to predict outcomes in surgically treatable cases by analyzing radiomics data from preoperative CT scans along with clinical factors, while the model outperformed the TNM staging. These studies suggest that pre-operative imaging alone does not provide enough information to accurately predict prognosis. Indeed, the addition of CA 19-9 in a model proposed by Watson et al. was correlated with an increased accuracy of two (pure and hybrid) DL models in predicting pathological response in PDAC patients [91]. Therefore, it is recommended to integrate other data modalities, such as clinical variables, histopathology, genomics, and additional imaging techniques, to improve prognostic predictions. Lastly, other features of PDAC such as tumor-infiltrating lymphocytes, lymph node metastasis, or specific cell populations infiltrating tumor microenvironment have also been successfully predicted using CT radiomics and DL [92–94].

For pancreatic neuroendocrine tumors (pNETs), the use of radiomics and CT has been studied for differentiating and classifying pancreatic tumors. Multiple studies assessed AI models capable of differentiating between pNETs and PDACs. He et al. [62] developed three models to distinguish between nonfunctional pNETs and PDACs based on a radiomics model improved through integration of clinical-radiological features. Li et al. [63] investigated the application of volumetric CT texture analysis in distinguishing atypical pNETs from PDACs. In a separate investigation conducted by Yu et al. [64], radiomics was employed to distinguish non-hypervascular pNETs from PDACs in a cohort of 120 patients. Accurate pre-surgical aggressiveness prediction of pNETs has been attained by Mori et al. based on radiomic features extracted by an ML model from preoperative contrast-enhanced CT images, separate or along with clinico-radiological features. The model was able to predict tumor grade, presence of distant metastases, metastatic lymph nodes, and microvascular invasion with moderate to high accuracy [95]. Several studies have also examined the feasibility of using CT-based texture analysis to predict the histological grade of a pNET [65, 66, 96, 97].

Diagnosis of pancreatic cystic lesions is a challenge. Nevertheless, the integration of macroscopic morphological features and texture analysis significantly enhanced the diagnostic accuracy in characterizing cystic lesions. The effectiveness of an AI model in differentiating between mucinous cystic neoplasms (MCNs) and serous cystic neoplasms (SCNs) was assessed by Yang et al. The same authors evaluated the capacity of CT texture analysis to differentiate between pancreatic serous cystadenoma (SCA) and mucinous cystadenoma (MCA), as well as enhance diagnostic accuracy by integrating morphological traits and textural attributes [68]. Shen et al. [69] examined the capability of CT to differentiate between various subtypes of pancreatic cystic neoplasms (PCNs). Additional research has concentrated on predicting the malignancy risk of IPMN, a condition that is difficult to manage due to the limited capacity of traditional imaging methods in detecting suspicious lesions. Hanania et al. [70] established a correlation between the histopathological grade of an IPMN and multiple radiomics markers located within the cyst boundaries.

While Chen et al. looked at the prediction of recurrence of acute pancreatitis [71], Mashayekhi et al. have attempted to assess whether a radiomics model could distinguish between acute and chronic pancreatitis [72]. Another application of AI in pancreatic CT imaging was proposed by Liang et al., who focused on

TABLE 3 | Summary of studies reporting on CT/MRI/EUS based AI applications for prognosis of pancreatic lesions.

Author	Imaging	Type of AI	Lesion type	Imaging datasets	Accuracy
Yimamu et al. [57]	CT	Human-machine fusion ML model	PDAC resectability prediction	349 patients from 4 centers	AUC: 0.884, Accuracy 82.5%, Sensitivity: 84.2%, Specificity: 82%
Bereska et al. [58]	CT	nnU-Nets network	Assess vascular involvement and resectability of PDAC	467 PDAC 50 control patients	Radiologists' agreement 76% for vascular involvement
				613 CT scans	80% overall agreement for resectability
Zhang et al. [88]	CT	Radiomics + deep learning (transfer learning) with 8-layered CNN	Survival prediction in resectable PDAC	68 patients (training) 30 patients (test cohort)	AUC: 0.84 (95%CI: 0.70–0.98), Specificity: 68%, Specificity: 91%
Zhang et al. [89]	CT	CNN	Survival prediction in resectable PDAC	Cohort 1: 422 patients with non-small cell lung cancer	Superior to traditional models for index of prediction accuracy (IPA): 11.89% versus 4.40%
				Cohort 2: 68 patients with resectable PDAC	
				Cohort 3: 30 patients with resectable PDAC (test)	
Yao et al. [60]	CT	ResNet3D with contrast enhanced convolutional long short-term memory network	Predict survival outcomes in resectable PDAC	Dataset A: 296 patients with PDACs	Harell's concordance index (*C*-index): 0.645
				Dataset B1 and dataset B2: 571 patients with PDACs and 61 patients with IPMNs	1-year overall survival AUC: 0.684 ± 0.013
				Dataset C: 281 patients with pancreatic tumor	2-year overall survival AUC: 0.689 ± 0.023
				Datased D: 90 patients with 17 classes of pixel-level organ and vessel annotations	
Toyama et al. [90]	PET/CT	Radiomics + machine learning	Predict outcomes in pancreatic cancer	161 PDAC patients	Not specified - 2 radiomic features identified as the most relevant discrimination factors for overall survival
Watson et al. [91]	CT	Pure and hybrid deep learning models	Predict response to neoadjuvant therapy in PDAC	81 patients 776 CT images	AUC: 0.738 for pure DL model
					AUC: 0.785 for hybrid DL model (incorporating CA 19-9 10% decrease)
Bian et al. [92]	CT	XGBoost machine learning	Predict tumor-infiltrating lymphocytes in PDAC	183 PDAC patients	AUC: 0.73 (95%CI: 0.65–0.92), Sensitivity: 63%, Specificity: 91%
Bian et al. [93]	CT	CNN	Predict lymph node metastasis in PDAC	734 PDAC patients	AUC: 0.92

(Continues)

TABLE 3 | (Continued)

Author	Imaging	Type of AI	Lesion type	Imaging datasets	Accuracy
Yu et al. [94]	CT	Multilayer perceptron network classifier	Predict CD20 (+) B cells infiltration in PDAC	189 PDAC patients	AUC: 0.84 (95%CI: 0.72–0.93), Sensitivity: 86.2%, Specificity: 78.5%
Mori et al. [95]	CT	Machine learning	Predict aggressiveness of pNENs	101 patients	AUC: 0.61 to 0.81 for different agressiveness factors (presence of distant metastasis, metastatic lymph nodes, vascular invasion, tumor grading G1 vs. G2/3)
Luo et al. [96]	CT	CNN	Predict pathological grading of pNENs	93 patients	AUC: 0.82 highest for G3 lesions
Javed et al. [97]	CT	Random forest model	Predict histologic grade of NF-pNETs	270 patients	AUC: 0.69, sensitivity: 80% for G2/3 lesions, superior tot EUS-FNA
Liang et al. [98]	CT	DenseNet CNN	Predict severity of acute pancreatitis	1561 acute pancreatitis patients	AUC: 0.980 for severe acute pancreatitis
Chen et al. [99]	CT	Deep learning/CNN	Predict severity of acute pancreatitis	978 acute pancreatitis patients	AUC: 0.920 (95%CI: 0.87–0.95) for severe acute pancreatitis
Kambakamba et al. [100]	CT	Machine learning	Predict postoperative pancreatic fistula	110 patients	AUC: 0.95, sensitivity: 96%, specificity: 98%
Mu et al. [101]	CT	Deep learning	Predict postoperative pancreatic fistula	513 patients	AUC: 0.89 (95%CI: 0.79–0.96)
Kaissis et al. [102]	MR	Random forest classifier	Predict overall survival in PDAC	132 PDAC patients	AUC: 0.90, sensitivity: 87%, specificity: 80% for survival prediction
Xie et al. [103]	MR	Machine learning	Predict pathological outcomes in pancreatic cancer	166 PDAC patients	AUC: 0.892 for histological grade and 0.875 for lymph node metastasis
Yuan et al. [104]	MR	Radiomics	Predict liver metastasis in PDAC	148 PDAC patients	Accuracy: 0.832
Li et al. [105]	MR	Multilayer perceptron classifier (MLPC)	Predict CD20+ B-cells in PDAC	156 PDAC patients	AUC: 0.79, Sensitivity: 69.2%, Specificity: 80.9%
Skawran et al. [106]	MR	Logistic regression + gradient boosted tree (GBT)	Predict postoperative pancreatic fistula	62 patients	AUC: 0.90 (95%CI: 0.84–0.95)
Facciorusso et al. [107]	EUS	ANN /logistic regression	Predict pain response after celiac plexus neurolysis (CPN) and need for repeat CPN	156 patients	AUC: 0.94 for ANN, superior to 0.85 for logistic regression
Huang et al. [108]	CEUS	Deep learning + nomogram	Predict aggressiveness of pNENs	104 patients (84 training set, 24 test set)	AUC: 0.85 (95%CI: 0.69–1.00)
Schulz et al. [109]	EUS	Deep learning (transfer learning)	Risk stratification for IPMNs	3355 EUS images from 43 patients	Accuracy: 99.6%

(Continues)

TABLE 3 | (Continued)

Author	Imaging	Type of AI	Lesion type	Imaging datasets	Accuracy
Machicado et al. [110]	EUS-needle based CLE	CNN	Risk stratification for IPMNs	15,027 video frames from 35 consecutive patients with histopathologically proven IPMNs (18 with High grade dysplasia/ Adenocarcinoma)	Sensitivity: 83.3%, Mean specificity: 85.3%

predicting the severity of acute pancreatitis using enhanced CT scans analyzed by CNN, showing significant predictive capabilities in terms of both CTSI and Atlanta classifications [98]. A more recent study explored the application of DL to predict the severity of acute pancreatitis (AP) early in its progression on non-enhanced CT scan images [99].

A fearful complication after surgery for PDAC is known to be pancreatic fistula. Predicting this complication is an important area where AI could contribute. Thus, ML techniques have been shown to improve surgical outcomes by analyzing complex datasets to predict patient outcomes, optimize surgical planning, and personalize postoperative care [100]. The predictive ability of a ML-based texture analysis with the original and alternative risk scores for pancreatic fistula after pancreatic surgery shows a clear superiority of the former [100, 101]. This effect is attributable to ML's ability to detect features like histologic fibrosis, histologic lipomatosis, and intraoperative pancreatic hardness that negatively impact surgical outcomes. The AI role becomes most important in intermediate-risk patients where traditional fistula risk scores perform worst.

5.2 | Magnetic Resonance

MRI is a valuable tool for analyzing both cystic and solid tumors as it enables the examination of the pancreatic ducts, pancreatic tissue, nearby soft tissues, and blood vessels.

Most research on the radiomics of MRI has primarily concentrated on distinguishing normal tissue from pancreatic tumors as well as predicting treatment outcomes and overall survival [102]. Thus, a supervised ML algorithm was developed to predict above-versus below-median overall survival (OS) in patients with PDAC using radiomic features derived from diffusion-weighted imaging. The use of multiparametric MRI radiomics has been investigated to predict lymph node metastasis and other survival-related features in PDAC patients, based on the extraction of texture features from both peritumoral and intratumoral regions, which served as the base for the training of six classifiers, aiming to enhance the accuracy of preoperative evaluations to predict key pathological characteristics such as tumor grade, lymph node involvement, and overall survival [103]. Another important survival-related parameter is the development of liver metastasis. AI models using MRI radiomics and serological markers used in combination showed promising results in a recent study [104]. Other survival-related applications of MRI-based ML models are related to the cell populations that infiltrate the tumor. In this regard, a multilayer perceptron classifier was trained on non-contrast MRI scans to non-invasively predict CD20 expression, which is a potential therapeutic target in PDAC and a predictor of survival [105]. The classifier demonstrated promising accuracy with an AUC of 0.79.

MRI findings, such as tumor margins, texture, local invasion or metastases, tumor enhancement, and diffusion restriction, along with texture parameters, can help predict the grading of pNETs, as demonstrated by Guo et al. [73]. The significance of radiomics parameters obtained from MRI scans in distinguishing between hypovascular nonfunctional pancreatic neuroendocrine tumors and solid pseudopapillary neoplasms of the pancreas has also been evaluated [74]. A nomogram composed of age and arterial phase radiomic feature signature performed best with AUC of over 0.9 in both training and validation cohorts [75].

When assessing cystic lesions using MRI, a difficulty arises in the examination of IPMNs and accurately determining the probability of malignant transformation. Multiple studies have examined the utilization of MR radiomics signatures to accurately predict the likelihood of malignancy in IPMNs solely through texture analysis or by combining clinical and radiological characteristics [76]. Enhancing mural nodule size $\geq$ 5 mm and dilated main pancreatic duct are independent predictors of malignant IPMNs, with the information derived from MRI. The addition of MR texture analysis can improve the prediction of malignant IPMNs.

A radiomics model that utilizes contrast-enhanced MRI on portal venous phase images seems to accurately predict the severity of acute pancreatitis, even in its early stages [77]. The AUC of the radiomics model, APACHE II, BISAP, and MRSI were 0.848, 0.725, 0.708, and 0.719, respectively, with the radiomics model that yielded good performance in the early prediction of AP severity. Frøkjaer et al. conducted a study to evaluate the use of texture analysis in MRI scans of 77 patients with chronic pancreatitis and 22 healthy controls [78]. The study found that the classification of chronic pancreatitis versus healthy controls had a sensitivity of 97%, specificity of 100%, and accuracy of 98%.

Similarly to CT, the use of MRI radiomics, more specifically gradient-boosted trees (GBT), was challenged to predict postoperative pancreatic fistula, demonstrating the potential of MRI features to improve prognostic assessments [106]. The model achieved AUC of 0.75. However, combining the GBT with the pancreas-to-muscle T1 Si ratio augmented its AUC to 0.90.

5.3 | Endoscopic Ultrasound

Implementation of AI in real-time during EUS-guided procedures will provide the next great leap in the management of pancreatic diseases. The ability to enhance diagnostic EUS with AI to stratify lesion likelihood to be malignant and to define precise targets for therapy will greatly increase utilization of EUS for both diagnosis and therapy. Other potential applications include tracking tumor progression, assessing treatment response, and predicting patient outcome.

Most of the research focused on differentiating PDAC from chronic pancreatitis (CP) using EUS images, showing a high accuracy when using an AI algorithm [112, 113]. AI can identify patterns in data which may not be obvious to the human eye and is able to construct predictive models for diagnosis, prognosis, and treatment response. Several studies still used EUS images for the automatic diagnosis of focal pancreatic masses [79–81]. However, at this moment, there is no standardized protocol regarding data collection, image processing, and analysis, while in most of the studies there is a lack of external validation. One study aimed to develop a DL radiomics (DLR) model using EUS images to identify PDAC and assess its clinical utility. Results showed that the DLR model achieved high diagnostic performance with an AUC of 0.936. DLR assistance significantly improved the diagnostic accuracy, particularly enhancing the performance of junior endosonographers to be comparable with their senior counterparts [79]. Kuwahara et al. used another CNN model (EfficientNet) based on EUS images and were able to distinguish between various types of pancreatic masses, achieving high diagnostic AUC (0.9) for the diagnosis of PDAC, although the study lacked external validation [80]. Tonozuka et al. evaluated their ML algorithm for classifying pancreatic masses using a dataset of 139 patients, achieving 92.4% sensitivity, 84.1% specificity, and 0.94 AUC with a CNN model on 470 test images, while also employing pseudo-colored feature mapping to enhance decision-making clarity for endosonographers [81]. A more recent study evaluated an ML model combining a custom-based CNN and Long Short-Term Memory (LSTM) networks to classify focal solid pancreatic lesions (PDAC vs. chronic pseudotumoral pancreatitis and pNETs) extracted from various types of EUS images (grayscale, color Doppler, arterial and venous phase contrast-enhancement and elastography) [82]. This approach achieved 98.1% sensitivity, 96.7% specificity, and 0.97 AUC for the diagnosis of PDAC in a population of 65 patients (1300 collected images increased to 3360 by various augmentation techniques), with diagnoses confirmed by histology and clinical follow-up. The ML approach was more complex as it combined two ML approaches with CNN and LSTM, allowing the inclusion of temporal data based on contrast-enhanced harmonic (CHI) EUS imaging, although the study lacked external validation. Another group developed a CNN model using EUS images to differentiate autoimmune pancreatitis (AIP) from PDAC, chronic pancreatitis (CP), and normal pancreas (NP), achieving 99% sensitivity and 98% specificity for AIP versus NP, 94% sensitivity, and 71% specificity for AIP versus CP, and 90% sensitivity and 93% specificity for AIP versus PDAC, potentially enabling earlier and more accurate diagnosis to improve patient care and outcomes [83]. Based on the performance and speed of newer CNN models, a real-time AI-enhanced system has been developed for the detection and segmentation of pancreas, cystic lesions and solid pancreatic masses [114].

More recently, a CAD system using contrast-enhanced EUS showed promising results for the diagnosis of pancreatic masses in real time [84]. This study aimed to develop a DL-based system, CH-EUS MASTER, to assist in diagnosing pancreatic masses using contrast-enhanced harmonic endoscopic ultrasonography (CH-EUS) and guiding EUS-guided fine-needle aspiration (EUS-FNA). The system achieved a diagnostic accuracy of 92.3%, sensitivity of 92.3%, and specificity of 92.3%, outperforming endoscopists who had an accuracy of 87.2%, sensitivity of 88.5%, and specificity of 84.6%. The system's positive predictive value (PPV) was 96.0% and negative predictive value (NPV) was 85.7%. During EUS-FNA, CH-EUS MASTER-guided procedures showed a first-pass diagnostic yield of 80.0% for malignancies, compared to 33.3% in the control group.

A prognostic application of AI for EUS was tested to predict patient need for repeat EUS-guided celiac plexus neurolysis (rCPN). Two ML algorithms, an ANN and a logistic regression one, were investigated for the ability to predict the pain response and the need for repeat EUS and rCPN for managing refractory pain in pancreatic cancer patients. The findings showed that ML models could accurately predict pain relief outcomes, with a superiority of the neural network in terms of AUC (0.94 vs. 0.85, $p < 0.001$).

Various ML algorithms based on EUS images were able to distinguish between pNET and PDAC in a recent study [85]. Ultrasomics features were extracted from EUS images, followed by dimensionality reduction using the Mann–Whitney test and least absolute shrinkage and selection operator (LASSO) algorithm. Besides differentiation from PDAC, prediction of tumor aggressiveness for pNETs has also been tested with AI, using a nomogram that integrates DL-derived features from contrast-enhanced ultrasound (CEUS) and clinical data pNETs [108]. The combined nomogram model that incorporated independent clinical risk factors such as tumor size, arterial enhancement level, and DL predictive probability demonstrated high accuracy with an AUC of 0.85.

In the setting of pancreatic IPMN, it has been shown that there is only moderate interobserver agreement with EUS and cyst fluid analysis for distinguishing benign from malignant lesions [115, 116]. Given the indolent nature of low-grade dysplasia IPMN and the associated risk of surgical overtreatment [117], the ability to better characterize IPMN with EUS is an important goal. Vilas-Boas et al. developed a CNN algorithm based on 28 cystic pancreatic lesions and 5505 EUS images. The Xception model with weights trained on ImageNet achieved 98.5% accuracy, 98.3% sensitivity, 98.9% specificity, and an AUC of 1, with an image processing speed of 7.2 ms per frame, effectively differentiating mucinous from non-mucinous cysts to aid in risk stratification of PCLs [86]. Another study investigated the effectiveness of a DL algorithm for diagnosing malignancy in IPMNs using EUS images [87]. The retrospective analysis included EUS images processed using a CNN based on ResNet50 architecture. Results showed that the AI algorithm had a significantly higher accuracy (94.0%) in predicting malignancy compared to the doctor's diagnosis (56.0%) and conventional methods. Preoperative risk stratification based on histological dysplasia grading has been tested with DL models in a study that used transfer learning to fine-tune a CNN to analyze and distinguish between low-grade and high-grade/invasive carcinoma IPMNs, achieving an impressive accuracy of 99.6% and significantly outperforming current international consensus guidelines, which have accuracies ranging from 51.8% to 70.4% [109]. An interesting approach for risk stratification of IPMNs was proposed by Machicado et al. [110]. The research team designed two CNN algorithms capable of analyzing confocal laser endomicroscopy (CLE) images that were compared with the American Gastroenterological Association and the revised Fukuoka guidelines through means of sensitivity and specificity. Compared to the guidelines, both models yielded higher sensitivity (83.3% both CAD-CNNs vs. 55.6% both guidelines) with comparable specificity for diagnosing high-grade dysplasia/adenocarcinoma.

6 | Diagnosis Confirmation

Therapeutic approaches and prognoses for PDAC/PNEN significantly differ from those for benign pancreatic masses. Therefore, accurate pathological diagnosis of pancreatic tumors is crucial for determining the most effective therapeutic strategy. AI systems based on DL models can offer significant assistance to the pathologists in assessing pancreatic lesions. In contrast to the pathologist, DL models typically require a shorter training time and exhibit greater objectivity. AI has also been employed in the field of EUS-FNA/B, significantly advancing automated pathological image diagnosis.

In the first study using EUS-guided FNA specimens for cytological analysis, Momeni-Boroujeni et al. used a K-means clustering algorithm and a multilayer perceptron neural network (MNN) to classify pancreatic samples as either benign or malignant [118]. The AI algorithm showed a 100% accuracy rate in discriminating between benign and malignant pancreatic cytology, while achieving a 77% accuracy rate for the atypical dataset. Furthermore, Kurita et al. combined biomarkers, cytological analysis, and clinical data to differentiate malignant from benign pancreatic cystic lesions using an AI algorithm, surpassing traditional methods in sensitivity and accuracy. The findings of this study demonstrated that AI has significantly higher sensitivity than pancreatic cyst fluid analysis in distinguishing between malignant and benign cystic lesions [119]. Hyperspectral imaging (HSI) is a new optical diagnostic technology that combines spectroscopy to measure the interaction between tissues and light through an HSI camera [120]. The HSI-based CNN model achieved high accuracies on both internal (92.04%) and external (92.27%) test datasets, by using informative spectral features to differentiate benign and malignant pancreatic cytology.

One study developing a DL model for confirmation of PDAC in rapid on site cytopathological evaluation (ROSE) during EUS-FNA was conducted by Zhang et al. [121]. This retrospective study using a novel deep CNN achieved an accuracy of 94.4% on the internal testing dataset. Furthermore, the system showed robust generalization on external testing datasets with accuracies ranging from 91.2% to 95.8%. Similarly, in the same year, Lin et al. introduced an AI model designed to replace ROSE during EUS-FNA [122]. The accuracy in the internal validation dataset was 83.4% and 88.7% in the external validation dataset, showing that AI can make ROSE accessible in more hospitals.

The introduction of EUS-guided FNB needles enabled the acquisition of larger tissue samples with fewer needle passes. Therefore, a retrospective study conducted by Naito et al. assessed pancreatic cancer using FNB whole slide images (WSI) with a CNN, achieving an AUC of 0.984 [123]. Likewise, Ishikawa et al. presented a new AI-based system for evaluating EUS-FNB samples in pancreatic lesions using DL and contrastive learning [124]. This model attained a similar accuracy rate (84.4%) to endoscopists in assessing the diagnostic quality of EUS-FNB specimens in macroscopic on-site evaluation (MOSE), which involves the visual assessment of samples collected during EUS-FNA/B procedures. The use of AI for directing targeted EUS-FNA/FNB procedures is a novel field but shows great potential for more accurate sampling, avoiding necrotic areas and allowing less needle passes. A new combination of CH-EUS and EUS-FNA/B can provide subtle parenchymal changes and thus guide puncture sites [125].

7 | Challenges and Limitations

AI in pancreatic imaging holds tremendous promise, yet several challenges and limitations must be addressed to fully highlight its potential. One of the hurdles is the quality and quantity of data available for training AI models. High-quality annotated datasets are essential, but they are often scarce due to the complexity of pancreatic anatomy and variability in CT/MR/EUS imaging protocols across different institutions. For example, several published studies used the NIH pancreas CT dataset (https://www.cancerimagingarchive.net/collection/pancreas-ct/) [14, 20–22, 30, 31, 33, 34] which is limited to 80 patients with contrast-enhanced 3D CT scans. Although larger datasets are available (for e.g., the Medical Segmentation Decathlon or DeepLesion from NIH), specific usage for pancreatic imaging has scarcely been reported [30]. Moreover, the ground truth (gold standard) for training is usually represented by high-quality validated data or expert annotations used to train the models [126]. Manual expert annotations are provided by multiple radiologists with consensus labeling in cases with significant differences. However, there is an important effect of interobserver variability on segmentation, especially for tumor delineation, as the lesions can be heterogenous and similar to the surrounding background [127]. Employing automatic or semi-automatic segmentation algorithms might reduce these differences [128].

The generalizability of AI models is another concern. Models trained on specific datasets may not perform well on data from different populations or imaging protocols, leading to potential biases. Technical limitations also impact the effectiveness of AI in pancreatic imaging. Variability in pancreatic shapes and sizes, the soft and deformable nature of pancreatic tissue, and indistinguishable margins from surrounding organs contribute to inaccuracies in automated segmentation and detection tasks. This complexity demands sophisticated algorithms capable of handling such variability. Thus, only a few DL algorithms have been validated prospectively on external data using various methodologies [31, 49–53, 56, 76, 121]. Also, even though there are specific algorithms available on the market designed to improve early detection rates, enhance segmentation, and support clinical decision-making, most of these are insufficiently tested on external data. To the best of our knowledge, there are no published clinical studies that directly compare the performance of commercially available algorithms for pancreatic cancer detection in a head-to-head fashion. While individual algorithms have been clinically validated and some have been measured against standard diagnostic practices, direct comparisons between different pancreas imaging AI algorithms within a clinical setting are limited. A recent systematic review looked upon the randomized control trials (RCTs) using AI and found that most of these are linked with colonic polyps or gastric lesions, none being performed for pancreatic diseases [129]. However, the clinical relevance of these methods will certainly impact pancreatic imaging, the transition being rapid toward integration in daily practice [130].

Integrating AI into clinical workflows requires substantial changes in infrastructure and extensive training for healthcare professionals. The adaptation process is often slow and resource-intensive, demanding rigorous validation in real-world clinical settings before AI tools can be widely adopted. Moreover, regulatory and ethical considerations pose significant challenges. Ensuring patient data privacy, securing consent for data usage, and addressing the ethical implications of AI-driven decisions are critical for compliance with regulations such as GDPR and HIPAA. In this context, human AI interaction in diagnosing pancreatic diseases will certainly focus on how clinicians utilize AI and DL tools designed to assist in the detection, diagnosis, and management of conditions such as pancreatic cancer and pancreatitis. For example, in the study by Park et al. [53], researchers examined the effect of integrating AI assistance on radiologists' performances. They assessed the impact of human-machine collaboration by comparing diagnostic accuracy, sensitivity, specificity, and reading times between AI-assisted readings and those performed without AI support.

8 | Future Directions and Trends

The main challenge for effective machine learning applications in pancreatic lesions is the lack of large datasets of patients with early pancreatic subtypes and an unequivocal “ground truth” for testing algorithms. The complex nature of medical image perception should mean that AI solutions are designed to augment the decision-making of expert clinicians and thus be subjected to equally rigorous testing prior to a clinical application. In the context of future AI applications, cooperation between academia, industry, and multi-site international collaborations of expert clinicians is crucial for data sharing, testing large-scale deep learning models, and the development of regulatory policies. Moreover, most studies focus on detection of lesion compared to characterization due to the difficulty in the latter; therefore, future studies must aim to classify different lesion subtypes and their malignant potential. Also, the majority of existing studies are retrospective in nature and rely on static images or video recordings. It is imperative to increase the number of prospective studies capable of evaluating the real-time performance of AI systems. Validation and benchmarking are thus crucial for ensuring the reliability of AI models. Despite promising results from many studies, large-scale multicenter trials are necessary to validate AI performance across different clinical settings.

9 | Conclusion

In conclusion, the synergy between AI and pancreatic imaging represents a paradigm shift in the management of pancreatic lesions, offering unprecedented diagnostic accuracy, monitoring capabilities, and personalized treatment strategies. If computer vision AI models can provide a way to perform “virtual pathology” with high diagnostic accuracy, this would be a great advantage given the current limitations, high cost and associated risks of the procedures.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.