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The Application of Artificial Intelligence in the Early Screening of Pancreatic Cancer

Yunwen Song

Beijing Haidian District Daoxianghu School, Beijing, China
h2027167@thisdl.cn

Abstract. This paper focuses on the application of artificial intelligence (AI) in the early screening of pancreatic cancer, a highly lethal malignancy known as the "king of cancers." With an overall 5-year survival rate of only 11% and 80% of patients diagnosed at an advanced stage, effective early screening is critical to improving prognosis. Key findings show that AI-aided computed tomography (CT), endoscopic ultrasound (EUS), magnetic resonance imaging (MRI), and liquid biopsy achieve high detection accuracy: the PANDA model (non-contrast CT) detects pancreatic ductal adenocarcinoma (PDAC) with an area under the curve (AUC) of 0.986–0.996; multimodal EUS-AI improves novice endoscopists' diagnostic accuracy to 0.90; MRI radiomics nomograms predict high-grade lesions with AUC 0.88–0.90; liquid biopsy AI models (cfDNA multi-omics, 5hmC) reach AUC 0.92–0.99.AI enables earlier, more accurate, and minimally invasive screening, addressing limitations of conventional tools and providing a promising basis for integrating AI into clinical pancreatic cancer screening programs.

Keywords: Pancreatic cancer, early screening, artificial intelligence, medical imaging

1. Introduction

Although pancreatic cancer ranks seventh among global cancers, it is known as the "king of cancers." Despite decades of scientific advances in treatment, its mortality rate remains close to its incidence, and its 5-year survival rate still hovers around 11% [1]. More than 80% of patients are already at an advanced stage when diagnosed, losing the chance for curative surgery. The main reason is the lack of effective early screening methods and typical early symptoms. It is predicted that by 2030, PDAC will become the second leading cause of cancer death. Pancreatic cancer's high lethality is closely related to its insidious onset—early lesions are small, lack specific clinical symptoms, and are difficult to detect with conventional screening tools, leading to missed optimal treatment opportunities [1, 2].

Studies show that patients who undergo early detection have a median survival of 9.8 years, much higher than the 1.5 years for those not screened [3]. However, there are currently no biomarkers with sufficient sensitivity and specificity for accurate clinical diagnosis of pancreatic cancer. The only serum biomarker approved by the U.S. Food and Drug Administration, CA19-9, lacks sufficient specificity and therefore does not support large-scale early screening for pancreatic cancer [2]. CA19-9 can be elevated in benign diseases such as chronic pancreatitis and biliary tract

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infections, resulting in false positives, while some early PDAC patients have normal CA19-9 levels, leading to false negatives [2].

Faced with the growing healthcare burden of pancreatic cancer, conventional imaging modalities still have obvious deficiencies in early detection and accurate diagnosis. Traditional screening tools such as CA19-9, conventional CT and EUS have limitations including insufficient sensitivity and specificity, and heavy reliance on operator experience, which makes early detection of pancreatic cancer difficult. In recent years, artificial intelligence has gradually entered the field of medical image analysis for pancreatic cancer [4]. AI can automatically extract imaging features and detect early subtle lesions that are difficult to detect with the naked eye. These advances point the way toward improving diagnostic accuracy and achieving personalized treatment for diseases such as pancreatic cancer. The four key technical fields (CT, EUS, MRI, and liquid biopsy) selected in this review are clinically commonly used, have high research popularity in AI application, and show great potential in improving early screening effect. CT is widely used in general population screening due to its convenience and low invasiveness; EUS is the gold standard for detecting small pancreatic lesions but requires experienced operators; MRI has high soft-tissue resolution, suitable for lesion grading; liquid biopsy is minimally invasive and suitable for dynamic monitoring, making the four modalities complementary in clinical practice [4].

This paper summarizes recent advances in artificial intelligence for the early screening of pancreatic cancer, focusing on four technological areas: CT, EUS, MRI and liquid biopsy. For each imaging modality, discussions cover model architecture, key performance metrics and multicenter validation results. Current challenges, including insufficient external validation and poor model interpretability, are also analyzed. Furthermore, the pathways to promote clinical translation are explored, offering a reference for the practical application of AI in frontline pancreatic cancer screening. Through systematic collation of AI applications in the above fields, this paper clarifies the current research status, summarizes existing strengths and limitations, and provides theoretical guidance for future clinical research and practical implementation.

2. AI application in early pancreatic cancer screening

2.1. CT and AI

Compared with traditional contrast-enhanced CT, deep learning-based image analysis has far exceeded its limitations. Such models can accurately identify pancreatic ductal adenocarcinoma (PDAC) and, more importantly, detect hidden lesions months before they become visible to the naked eye. This opens up new possibilities for pancreatic cancer screening. Conventional contrast-enhanced CT depends on manual interpretation of tumor size, shape, and enhancement pattern, which vary considerably with the readers' experiences; consequently, small or faint early lesions frequently go unnoticed. Deep learning models, in contrast, can automatically extract high-dimensional imaging features that are difficult for human to spot, significantly improving the detection rate of early PDAC.

It was once believed that non-contrast CT had insufficient soft-tissue contrast to reliably diagnose pancreatic cancer. However, the PANDA model developed by Cao et al. changed this perception [5]. This model can detect the seven most common pancreatic lesions types and further classify their subtypes. The model consists of three stages: first, locating the pancreas; second, detecting any suspicious lesions; and third, distinguishing among different lesion types. The researchers trained the PANDA model on real-world clinical data. The internal training set included 3,208 patients, and the multi-center external validation set included 5,337 cases from various hospital. The model

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achieved an AUC of 0.986–0.996 for PDAC identification. When targeting small T1-stage tumors (diameter under 2 cm), it achieved a sensitivity of 85.7%–92.2% and a specificity of 97.3%. These results were significantly better than the average performance of 33 radiologists with varying levels of experience. The PANDA model's advantage lies in its ability to use non-contrast CT, which is more widely available in primary hospitals and avoids the risks of contrast agent allergies, thus lending itself well to large-scale screening of the general population.

In a separate effort, Korfiatis and co-workers built a fully automated 3D convolutional neural network (3D CNN) [6]. This model uses algorithmically generated pancreatic bounding boxes and segmentation masks as a two-channel input. The training data consisted of 1,105 diagnostic CT scans of PDAC patients and 1,909 control scans from people without pancreatic disease. On the internal test set (409 PDAC vs. 829 controls), the model produced an AUC of 0.97 for PDAC detection, along with a sensitivity of 0.88 and a specificity of 0.95. Notably, the sensitivity for T1-stage small tumors was 0.80, whereas for T4-stage tumors it reached 1.0. CT slice thickness, scanner vendor, patient age, and sex did not significantly affect the results. More importantly, the model performed well on 100 pre-diagnostic CT scans. These CT scans were incidentally obtained 3–36 months before clinical diagnosis and showed no definite lesions on routine reading. On these images, the model attained an AUC of 0.91, a sensitivity of 0.75, and a specificity of 0.90, spotting tumors a median of 475 days ahead of the clinical diagnosis. This demonstrates that an AI model trained only on routine diagnostic CT scans can capture early imaging changes invisible to the human eye long before clinical diagnosis. This finding is of great clinical significance, as it means that AI can use existing routine CT data to achieve early warning of pancreatic cancer without additional screening costs.

2.2. EUS and AI

For the general public, CT combined with AI offers a workable route for early pancreatic cancer screening. But when it comes to high-risk individuals, endoscopic ultrasound (EUS) turns out to be a more precise tool. The trouble is, EUS diagnosis suffers from a heavy dependence on the operator's skill. Adding AI to the mix can compensate for that shortage and push diagnostic accuracy considerably higher. It can spot tiny lesions as small as 2–3 mm. Yet its accuracy varies enormously from one practitioner to another, with novice endoscopists having an accuracy rate 20–30% lower than experienced specialists. Multimodal artificial intelligence, by integrating EUS images with clinical information, significantly improves diagnostic performance and reduces the capability gap among physicians. High-risk populations of pancreatic cancer include those with a family history of pancreatic cancer, chronic pancreatitis, diabetes, and obesity.

Ordinary CNN models often ignore medical history and lack external validation. To fix this, Cui and colleagues built a multimodal AI system that merges EUS images with 36 clinical indicators—covering things like patient history, lab results, and radiology reports—to tell malignant lesions apart from benign ones [7]. In the internal validation, their combined model achieved an AUC of 0.996 and 98% accuracy, far exceeding a single CNN model. In tests from three external independent medical centers, the AUC stayed stable, ranging from 0.924 to 0.976. In real-world use, the model proved its clinical worth. With AI assistance, the diagnostic accuracy of novice endoscopists increased significantly from 0.69 to 0.90, reaching a level comparable to that of experienced specialists. That improvement means skills which traditionally take years to accumulate can be picked up by junior doctors much faster when AI is there to help. The multimodal design of this model fully considers the complexity of pancreatic lesions, and the integration of clinical features

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effectively reduces misdiagnosis that come from looking at images alone, which better mirrors how clinicians actually reason.

Meanwhile, Udriștoiu et al. took a different tack. They coupled a CNN with a long short-term memory (LSTM) network to sort out focal pancreatic masses using multi-sequence EUS images (grayscale, color Doppler, contrast-enhanced, and elastography) [8]. Their model achieved a sensitivity of 98.1%, a specificity of 96.7%, and an AUC of 0.97 for PDAC detection, beating the earlier multimodal model in sensitivity. But it focus heavily on EUS image features alone, without integrating clinical information, and its external validation data is relatively insufficient.Multi-sequence EUS images can provide comprehensive information on lesion texture, blood supply, and elasticity, and the CNN-LSTM model can capture temporal and spatial features of images, which is particularly advantageous in distinguishing malignant lesions with complex morphological characteristics.

Marya's group also crafted a CNN model, this one aimed at separating autoimmune pancreatitis (AIP) from PDAC, chronic pancreatitis (CP), and normal pancreas (NP) using EUS images [9]. The model was trained on 583 patients and 1.17 million EUS images. The results: for distinguishing AIP from NP, sensitivity hit 99% and specificity 98%; for distinguishing AIP from CP, those numbers were 94% and 71%; and for the toughest challenging distinction between AIP and PDAC, sensitivity was 90% and specificity 93%. This high specificity helps clinicians avoid mistaking AIP for a malignant tumor, thus sparing patients unnecessary surgery and steering them toward more timely, appropriate treatment. AIP is a rare autoimmune disease that is clinically easily misdiagnosed as PDAC, and misdiagnosis often leads to unnecessary pancreatic resection, which seriously affects patients' quality of life. This model provides a reliable tool for differential diagnosis, improving the accuracy of clinical decision-making.

2.3. MRI and AI

Magnetic resonance imaging (MRI), combined with radiomics and machine learning, can extract tumor heterogeneity information from quantitative imaging features. This allows a non-invasive, fairly accurate prediction of preoperative grades for pancreatic cystic growths, particularly branch-duct intraductal papillary mucinous neoplasms (BD-IPMNs). Because such cystic lesions carry a substantial risk of turning malignant, getting the grading right before surgery is essential for deciding on a treatment plan. BD-IPMNs make up about 60–70% of all pancreatic cystic neoplasms, and their rate of malignant transformation falls somewhere between 10% and 30%. That's why early screening and accurate grading prediction matter so much.

Cui et al. used data from 202 BD-IPMN patients from three medical centers [10]. From MRI scans they extracted nine radiomic features and built a model to predict lesion grade. TIn the training cohort, that model gave an AUC of 0.836 for spotting high-grade lesions; in two separate external validation groups, the AUC came out at 0.811 and 0.822. Multivariate logistic regression analysis confirmed that main pancreatic duct diameter and CA19-9 level were independent predictors of high-grade lesions. The researchers combined these two clinical indicators with the radiomic signature to build a combined nomogram. That nomogram produced AUCs of 0.903, 0.884, and 0.876 in the training set and the two validation cohorts respectively—clearly outperforming any single clinical indicator on its own. The combined nomogram integrates imaging features and clinical indicators, which not only improves prediction accuracy but also has strong clinical operability, as main pancreatic duct diameter and CA19-9 are routine clinical inspection indicators.

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Jeon et al. systematically analyzed the predictive value of conventional imaging signs and texture parameters for malignant IPMN using MRI data from 248 patients [11]. Their univariate analysis identified several independent predictors: enhancing mural nodules (≥5 mm), main pancreatic duct dilatation (either ≥10 mm, or 5–9 mm with an abrupt change in caliber), and texture features like increased entropy or decreased homogeneity. When texture parameters were added to the conventional MRI signs, the diagnostic performance for predicting malignant IPMN improved markedly—from 0.80 and 0.78 up to 0.85 and 0.85 for the two readers. This study demonstrates that MRI texture analysis can serve as an effective supplement to conventional image interpretation, helping to improve the preoperative accuracy of assessing malignant risk in IPMNs. Conventional MRI signs are mainly based on visual observation, which is subjective and easily affected by operator experience, while texture parameters can objectively reflect tumor heterogeneity, providing more accurate quantitative indicators for malignant risk assessment.

Schulz's group employed a transfer learning strategy to fine-tune a convolutional neural network [12]. They trained the model on 3,355 EUS images from 43 IPMN patients and then externally validated it on 1,823 independent EUS images from 27 patients. This deep learning model achieved a classification accuracy of 99.6% when distinguishing low-grade dysplasia from high-grade dysplasia or invasive carcinoma—far surpassing any single international consensus guideline, whose accuracies typically range from 51.8% to 70.4%. Granted, this study used EUS images, but its transfer learning method has strong cross-modality transferability and could be extended to MRI. That opens up a new technical avenue for MRI-based IPMN grading prediction. Transfer learning also helps tackle the problem of scarce MRI data for rare pancreatic diseases like IPMN, cuts down on model training expenses, and could speed up the clinical adoption of AI models. Although this study used EUS images, its transfer learning method has good cross-modality transferability and can be extended to MRI, providing a new technical idea for MRI-based IPMN grading prediction. Transfer learning can solve the problem of insufficient MRI data for rare diseases such as IPMN, reduce model training costs, and accelerate the clinical application of AI models.

Overall, imaging AI is gradually becoming a mainstay of screening. Its impressive performance on routine exams such as non-contrast CT and EUS has created fresh opportunities for early detection. Among the three imaging modalities, CT and AI is more suitable for large-scale screening of the general population, EUS and AI is preferred for high-risk groups, and MRI and AI has obvious advantages in the grading prediction of pancreatic cystic neoplasms. Imaging AI models still need to be optimized for special populations, such as patients with liver cirrhosis or pancreatic fibrosis, to further improve their generalization ability.

2.4. Liquid biopsy and AI

Merging liquid biopsy with artificial intelligence is opening up fresh ways to catch pancreatic cancer early. This approach works alongside imaging-based AI screening, helping boost both sensitivity and specificity for early detection. By performing high-throughput analysis of markers such as cfDNA and extracellular vesicles (EVs) in the blood, combined with machine learning algorithms, researchers have successfully constructed early screening models with both high sensitivity and high specificity. Liquid biopsy has the advantages of non-invasiveness, repeatability, and ability to reflect the overall tumor status, which can make up for the limitations of imaging methods in detecting micrometastases and minimal residual disease (MRD), and is suitable for long-term dynamic monitoring of high-risk populations.

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2.4.1. cfDNA multi-omics and AI

Wu et al. constructed a pancreatic cancer diagnostic scoring system (PCM) by analyzing four features of plasma cfDNA: end motifs, fragmentation patterns, nucleosome footprints and copy number alterations [13]. The study involved a total of 975 participants—patients with pancreatic cancer plus healthy controls—and the model went through external validation in a multi-center cohort. The PCM score turned out to be very good at telling pancreatic cancer patients apart from healthy controls, with an AUC of 0.990. When the team looked specifically at resectable stage I or II tumors, the AUC climbed even higher, to 0.994. Using the same set of features, they also came up with a prognostic score (PCP). That score significantly separated patients by overall survival and recurrence-free survival, both in the training set and in the combined validation set—effectively linking early diagnosis with prognosis assessment. Because the PCM system pulls together multiple cfDNA omics features, it can capture a broad picture of the genetic and epigenetic changes happening in pancreatic cancer. Its high AUC speaks to strong diagnostic performance. By integrating diagnosis with prognosis, the tool becomes more clinically useful, helping doctors tailor treatment plans and follow-up schedules to each patient.

2.4.2. cfDNA hydroxymethylation and AI

Guler et al. used 5-hydroxymethylcytosine (5hmC) to perform genome-wide hydroxymethylation sequencing of plasma cfDNA [14]. With help from a regularized regression model, they set up a non-invasive way to detect PDAC. The study included 64 PDAC patients and 243 controls. The differentially hydroxymethylated genes they identified mostly turned out to be linked to pancreatic development (e.g., GATA4, GATA6) and cancer-related pathways (e.g., YAP1, TEAD1). The regularized regression model, which was built on 5hmC density, gave an AUC of 0.92 in the discovery set (n=79) and AUCs between 0.92 and 0.94 in two separate independent test sets (n=228). Even when they used only tumor-tissue-derived 5hmC features, the model still managed a respectable AUC of 0.88 for classifying PDAC cfDNA. These results indicate that cfDNA hydroxymethylation profiles can capture early epigenetic changes in pancreatic cancer, providing a new method for non-invasive screening of low-incidence tumors. Compared with the PCM score system, the 5hmC-based model has slightly lower AUC but is more focused on epigenetic changes, providing a new perspective for early screening. Epigenetic changes occur earlier than genetic changes in the process of tumorigenesis, so the 5hmC-based model may have unique advantages in detecting ultra-early pancreatic cancer, which is worthy of further in-depth research.

2.4.3. Extracellular vesicle RNA and AI

To achieve high-purity isolation of extracellular vesicles, Greenberg et al. developed pH-responsive nanomagnetic beads called ExCy [15]. By combining multiple machine learning algorithms to screen for pancreatic cancer-specific markers, the research team performed PCR validation on 22 plasma samples and successfully identified the ATP6V0B gene. This gene was significantly overexpressed in extracellular vesicles derived from pancreatic cancer patients. Three machine learning models achieved AUCs between 0.86 and 0.88 for early pancreatic cancer diagnosis. Additionally, the researchers proposed the Exosome Quality Index (EQI), a statistical algorithm for assessing EV isolation quality, which effectively improved the standardization and reproducibility of liquid biopsy research. This model has lower AUC than cfDNA-based models but has unique advantages in non-invasive sampling and dynamic monitoring, complementing other liquid biopsy-

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based AI models. EVs are rich in RNA, protein, and other biomolecules, which can reflect the biological characteristics of tumor cells. The ExCy nanomagnetic beads developed in this study solve the problem of low EV isolation purity, and the EQI index ensures the reliability of detection results, laying a foundation for the clinical application of EV-based early screening.

2.5. Summary of AI applications in four key fields

The four key technical fields of CT, EUS, MRI, and liquid biopsy have their own advantages and applicable scenarios in AI-aided early pancreatic cancer screening. CT and AI has high stability and wide applicability, making it suitable for large-scale screening of the general population. EUS and AI has high diagnostic accuracy, which is suitable for screening high-risk groups and making up for the deficiency of operator experience; MRI and AI is outstanding in the grading prediction of pancreatic cystic neoplasms, providing a basis for preoperative treatment decision-making; liquid biopsy and AI is minimally invasive and can realize dynamic monitoring, which is complementary to imaging-based screening. The common advantages of AI applications in these fields include high detection accuracy, ability to identify early subtle lesions, and reduction of human error; the common problems include insufficient external multi-center validation, poor model interpretability, and unclear clinical application standards. In clinical practice, a combined screening strategy based on these four modalities can be adopted: using CT and AI for large-scale general population screening, EUS and AI for further diagnosis of high-risk individuals, MRI and AI for lesion grading, and liquid biopsy and AI for dynamic monitoring, so as to improve the early detection rate and diagnostic accuracy of pancreatic cancer.

3. Conclusion

This paper has systematically walked through recent progress in using artificial intelligence for early pancreatic cancer screening, focusing on four key technical fields: CT, EUS, MRI, and liquid biopsy. The results show that AI-aided screening technologies have significant advantages over conventional screening methods in terms of detection accuracy, early lesion identification, and non-invasiveness. CT and AI models (e.g., PANDA, 3D CNN) achieve high AUC values in PDAC detection and can detect lesions months in advance; EUS and AI significantly improve the diagnostic accuracy of novice operators and enhance the differential diagnosis ability of pancreatic lesions; MRI and AI excel in the grading prediction of pancreatic cystic neoplasms, providing a basis for preoperative decision-making; liquid biopsy and AI (e.g., cfDNA multi-omics, 5hmC, EV RNA) realize non-invasive early screening and dynamic monitoring, complementing imaging-based screening. These advances have tackled many of the limitations that used to plague conventional screening tools, offering fresh ideas and methods for improving early detection rates and cutting down mortality from pancreatic cancer.

However, AI applications in early pancreatic cancer screening still face multiple challenges, including insufficient external multi-center validation, poor model interpretability, lagging clinical transformation, insufficient early-stage sample data, and high application costs. To promote the clinical application of AI in this field, it is necessary to strengthen multi-center cooperation, develop interpretable AI models, formulate unified clinical guidelines, expand sample size, reduce application costs, and strengthen clinician training. Looking ahead, as AI technology keeps advancing and multi-modal data become more deeply integrated, AI is likely to become an indispensable part of clinical early screening programs for pancreatic cancer—making personalized screening a reality and improving patient prognosis. All in all, AI has broad promise for early

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pancreatic cancer screening, and deeper research plus successful clinical translation will help lighten the global burden of this disease.

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