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AI-Driven Early Diagnosis of Pancreatic Cancer: Current Status and Future Perspectives

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Abstract: *Pancreatic cancer is a lethal disease characterized by a poor prognosis for patients, making early diagnosis crucial for improving patient survival rates. Artificial intelligence (AI), particularly exemplified by deep learning and radiomics, has provided new directions for the early diagnosis of this disease. This paper reviews the progress of AI based on Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Endoscopic Ultrasound (EUS) in the early diagnosis of pancreatic cancer. It specifically focuses on the value of end-to-end deep learning models and radiomics-based machine learning in differentiating pancreatic cancer from normal pancreatic tissue. Models such as Convolutional Neural Networks (CNNs), nnU-Net, and Vision Transformers have demonstrated pancreatic tumor detection rates ranging from 86.2% to 95.8%. Furthermore, by integrating mass signs with indirect imaging features like pancreatic duct dilation, the detection sensitivity for pancreatic cancers smaller than 2 cm has been improved to 70.7%-96%. Additionally, radiomics has shown potential in predicting tumor occurrence using CT images obtained 3 to 36 months prior to clinical diagnosis. Future research on image-based AI for early pancreatic cancer diagnosis should focus on multicenter prospective studies. The ultimate goal is to build intelligent diagnostic systems that are high-performing, robust, and interpretable, while seamlessly integrating into clinical workflows.*

Keywords: *Pancreatic Cancer, Radiomics, Artificial Intelligence, Deep Learning, Early Diagnosis*

1. Introduction

Pancreatic cancer (PC) is characterized by nonspecific early symptoms, high aggressiveness, and a tendency for metastasis, resulting in a poor prognosis for patients [1-3]. Its 5-year survival rate is approximately 13% [4-6], and less than 20% of patients are eligible for surgical resection at the time of diagnosis [7-9]. Therefore, early diagnosis of pancreatic cancer is critical for improving patient survival rates. Contrast-enhanced computed tomography (CT) and magnetic resonance imaging (MRI) are commonly used modalities for the diagnosis and staging of PC [10-12]. However, the pancreas is located deep in the retroperitoneum, surrounded by complex vascular and digestive tract structures. Small PCs often exhibit low contrast and atypical morphological features, posing significant challenges for early diagnosis [13-15]. The rate of missed diagnosis for pancreatic cancers smaller than 2 cm on CT scans can reach 40% [16,17,28,42]. Furthermore, the widespread application of high-resolution multi-slice spiral CT has led to a significant increase in data volume, adding to the workload of radiologists. Diagnostic outcomes are also subject to heterogeneity due to the varying experience levels of physicians [18]. Consequently, developing computer-aided diagnostic tools is of great value for enhancing the accuracy and efficiency of PC diagnosis.

Artificial intelligence (AI) has provided new technical pathways for assisting disease diagnosis. Models such as Convolutional Neural Networks (CNNs) and the recently emerging Vision Transformers can learn hierarchical representations from raw pixel data, capturing subtle differences in structure, texture, and enhancement patterns at multiple scales [19-22]. In pancreatic image analysis, these models have been utilized for tasks including pancreas/lesion segmentation, lesion detection, benign-malignant classification, and exploration of staging and prognosis modeling. In addition, interpretable radiomics methods, known for their low computational resource requirements, are also widely applied in disease diagnostic research [23,24].

Numerous studies have addressed the specific problem of "differentiating pancreatic cancer from

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normal pancreas." AI can overcome the accuracy limitations of traditional visual diagnosis and elucidate deep-level tumor features, such as image texture, holding significant clinical value for the early diagnosis and prediction of PC. Based on this, this review focuses on the research progress of AI driven by imaging data in distinguishing pancreatic cancer from normal pancreas. It systematically summarizes methods for pancreas and tumor segmentation and classification, and discusses the challenges and future directions for the clinical translation of AI diagnosis in pancreatic cancer.

2. Materials and Methods

A systematic literature search was performed using the PubMed database to identify articles concerning the application of artificial intelligence in the differential diagnosis of pancreatic cancer and normal pancreas. The search terms were used individually or in combination as follows: ("Computed Tomography" OR "Magnetic Resonance Imaging" OR "Endoscopic Ultrasound") AND ("Radiomics" OR "Artificial Intelligence" OR "Deep Learning" OR "Convolutional Neural Networks" OR "Machine Learning") AND ("Pancreatic Cancer" AND "Normal Pancreas"). The inclusion criteria were as follows: (1) original research articles published in English; (2) studies focusing on the differential diagnosis of PC versus normal pancreas based on imaging AI; and (3) relevant articles identified through the screening of reference lists of papers meeting the first two criteria. The exclusion criteria included case studies using qualitative methods, systematic reviews, scoping reviews, other literature reviews, editorials, commentaries, letters to the editor, conference abstracts, books, and book chapters. Ultimately, a total of 22 studies were included in this review (Table 1).

Table 1: The Characteristics of the articles included and the extracted data

Author / Year	Title	Aim	Sample	Imaging Modality	Machine Learning Model	Performance Metrics
Chen et al., 2023	Pancreatic Cancer Detection on CT Scans with Deep Learning: A Nationwide Population-based Study	To develop and validate a deep learning (DL)–based tool for detecting pancreatic cancer on CT.	Training/validation: 546 PC, 733 controls; Taiwan test: 669 PC, 804 controls.	CT (Venous phase)	Convolutional neural networks (CNNs) and an ensemble classifier including five CNNs	Sensitivity 89.7%; Specificity 92.8%
Saraiva et al., 2024	Deep Learning and Automatic Differentiation of Pancreatic Lesions in Endoscopic Ultrasound: A Transatlantic Study	To develop a CNN to detect and differentiate pancreatic cystic neoplasms (PCNs: mucinous and non-mucinous) and pancreatic solid lesions (PSLs), particularly PDAC and P-NET.	378 EUS: 64, 286 PDAC images, 4,858 normal images.	Endoscopic ultrasound (EUS)	Convolutional neural network (CNN)	Accuracy: normal pancreas 99.1%; PDAC 94.0%
Tonozuka et al., 2021	Deep learning analysis for the detection of pancreatic cancer on endosonographic images: a pilot study	To develop a computer-aided diagnosis (CAD) system using deep learning analysis of EUS images for PDAC detection.	76 PDAC, 34 CP, 29 normal.	Endoscopic ultrasound (EUS)	Convolutional neural network (CNN)	AUC 0.940
Ni et al., 2025	A convolutional neural network-based system for identifying neuroendocrine neoplasms and multiple types of lesions in the pancreas using EUS (with videos)	To develop a CNN-based system for identifying IPMN and multiple pancreatic lesion types using EUS.	573 patients	Endoscopic ultrasound (EUS)	Convolutional neural network (CNN)	PDAC accuracy: 86.2%
Yang et al, 2024	nnU-Net-Based Pancreas Segmentation and Volume Measurement on CT Imaging in Patients with Pancreatic Cancer	To develop and validate a DL-based method for pancreas segmentation on CT and automatic pancreatic volume measurement in pancreatic cancer.	499 PC, 352 normal.	CT (Venous phase)	nnU-Net	DSC: 0.764
Kawamoto et al., 2024	Deep neural network-based segmentation of normal and abnormal pancreas on abdominal CT: evaluation of global and local accuracies	To evaluate global and local accuracies of deep neural network (DNN) segmentation for normal and abnormal pancreas with pancreatic masses.	42 normal, 49 abnormal.	CT (Venous phase)	Deep neural network	Normal vs abnormal pancreas: DSC 87.4 vs 85.5; ASSD 0.97 vs 1.34; HD95 4.28 vs 6.31
Abi Nader et al, 2023	Automatic Detection of Pancreatic Lesions and Main Pancreatic Duct Dilatation on Portal Venous CT Scans Using Deep Learning	To evaluate a DL method for detecting pancreatic neoplasms and identifying main pancreatic duct (MPD) dilatation on portal venous CT scans.	2,185 pancreatic tumor, 705 healthy controls.	CT (Venous phase)	nnU-Net + logistic regression	AUC 0.98; Sensitivity 94%
Pan et al., 2024	Artificial intelligence-based tools with automated segmentation and measurement on CT images to assist accurate and fast diagnosis in acute pancreatitis	To develop an AI tool for automated segmentation and measurement of pancreatic morphology on CT images to improve and accelerate the diagnosis of acute pancreatitis.	Training set: 688; validation set: 145; test set: 104 normal, 98 AP, 89 AP&PDAC.	Non-contrast CT and contrast-enhanced CT	MSA-Net (CNN)	AP&PDAC AUC: improved from 0.85 to 0.92 in junior group; from 0.97 to 0.99 in senior group
Ozawa et al., 2025	Deep learning-based automatic detection of pancreatic ductal adenocarcinoma ≤ 2 cm with high-resolution computed tomography: impact of the combination of tumor mass detection and indirect indicator evaluation	To evaluate the diagnostic performance of a 3D CNN for automatic detection of small PDAC by combining tumor mass detection and indirect indicator evaluation.	100 PDAC, 104 controls	Contrast-enhanced CT	Convolutional neural network (CNN)	Sensitivity 96.0%
Ichikawa et al., 2025	The Usefulness of Low-Kiloelectron Volt Virtual Monochromatic Contrast-Enhanced Computed Tomography with Deep Learning Image Reconstruction Technique in Improving the Delineation of Pancreatic Ductal Adenocarcinoma	To evaluate whether low-energy (40 keV) virtual monochromatic imaging (VMI) combined with deep learning image reconstruction (DLIR) improves PDAC margin delineation compared with hybrid iterative reconstruction (HIR).	35 PDAC	Contrast-enhanced CT	Deep learning image reconstruction	Not reported
Ma et al., 2020	Construction of a convolutional neural network classifier developed by computed tomography images for	To automatically identify pancreatic cancer on CT images by constructing a CNN classifier.	222 PDAC, 190 normal controls.	CT	Convolutional neural network (CNN)	Accuracy: non-contrast phase 95.47%; arterial

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	pancreatic cancer diagnosis					phase 95.76%; venous phase 95.15%
Chen et al., 2021	Radiomic Features at CT Can Distinguish Pancreatic Cancer from Noncancerous Pancreas	To differentiate patients with pancreatic ductal adenocarcinoma (PDAC) from healthy controls.	Taiwan:536 PDAC, 579 healthy controls; U.S: 182 PDAC, 82 healthy controls.	CT (Venous phase)	XGBoost classifier	Sensitivity: 94.7% and 80.6%; Specificity: 95.4% and 100%; Accuracy: 95.0% and 86.5%; AUC: 0.98 and 0.91
Chang et al., 2023	Detection of pancreatic cancer with two- and three-dimensional radiomic analysis in a nationwide population-based real-world dataset	To develop an end-to-end computer-aided detection (CAD) tool based on two-dimensional (2D) and three-dimensional (3D) radiomic analysis combined with machine learning.	Training/validation: 546 PC, 733 controls; Taiwan test: 671 PC, 806 controls.	CT (Venous phase)	XGBoost, logistic regression	AUC 0.947; Sensitivity 91.8%; Specificity 82.2%
Mukherjee et al., 2022	Radiomics-based Machine-learning Models Can Detect Pancreatic Cancer on Prediagnostic Computed Tomography Scans at a Substantial Lead Time Before Clinical Diagnosis	To detect PDAC at the prediagnostic stage (3–36 months before clinical diagnosis) using radiomics-based ML models and compare their performance with radiologists in a case–control study.	Prediagnostic cohort (n = 155); control patients (n = 265).	CT (Portal venous phase)	K-nearest neighbor (KNN), support vector machine (SVM), random forest (RF), extreme gradient boosting (XGBoost)	Sensitivity 95.5%; Specificity 90.3%; F1 score 89.5%; AUC 0.98; Accuracy 92.2%
Chu et al., 2019	Utility of CT Radiomics Features in Differentiation of Pancreatic Ductal Adenocarcinoma From Normal Pancreatic Tissue	To determine the utility of radiomics features in differentiating PDAC from normal pancreas on CT images.	190 PDAC (97 men, 93 women) and 190 healthy controls.	CT (Venous phase)	Random forest (RF)	Accuracy 99.2%; AUC 99.9%
Chu et al., 2020	Diagnostic performance of commercially available vs. in-house radiomics software in classification of CT images from patients with pancreatic ductal adenocarcinoma vs. healthy controls	To compare commercially available radiomics software with in-house radiomics software in differentiating PDAC patients from healthy controls.	190 PDAC (97 men, 93 women) and 190 healthy controls.	CT (Venous phase)	Random forest (RF), minimum redundancy maximum relevance (mRMR)	Sensitivity 1.00; Accuracy 0.992
Koch et al., 2023	Multiparametric detection and outcome prediction of pancreatic cancer involving dual-energy CT, diffusion-weighted MRI, and radiomics	To evaluate the diagnostic and predictive value of a multiparametric approach combining radiomics texture analysis, DECT iodine concentration, and diffusion-weighted MRI (DWI) in patients with histologically proven pancreatic cancer.	83 PC, 20 pancreatitis, and 40 healthy.	DECT (Arterial phase), MRI-DWI	Euclidean distance matrices, t-distributed stochastic neighbor embedding (t-SNE), Cox proportional hazards model, intra-class correlation coefficients (ICC)	AUC ≥ 0.995
Ren et al., 2024	Computed tomography-based radiomics diagnostic approach for differential diagnosis between early- and late-stage pancreatic ductal adenocarcinoma	To evaluate the potential value of radiomics analysis in differentiating early-stage PDAC from late-stage PDAC.	71 PDAC	CT (Late arterial and portal venous phases)	Random forest (RF), leave-group-out cross-validation (LGOCV)	Accuracy 97.7%; Sensitivity 97.6%; Specificity 97.8%
Wang et al., 2022	Compute Tomography Radiomics Analysis on Whole Pancreas Between Healthy Individual and Pancreatic Ductal Adenocarcinoma Patients: Uncertainty Analysis and Predictive Modeling	To establish a predictive model distinguishing cancer patients from healthy individuals based on whole-pancreas radiomics features.	181 healthy controls and 85 cancer patients.	CT (Venous phase)	Random forest (RF), minimum redundancy maximum relevance (mRMR), leave-group-out cross-validation (LGOCV), univariate logistic regression	AUC 0.910; Accuracy 0.935
Mukherjee et al., 2024	Assessing the robustness of a machine-learning model for early detection of pancreatic adenocarcinoma (PDA): evaluating resilience to variations in image acquisition and radiomics workflow using image perturbation methods	To evaluate the robustness of a radiomics-based SVM model for detecting visually occult pancreatic ductal adenocarcinoma on prediagnostic CT scans.	155 PC (90 men, 65 women) and 265 controls (140 men, 125 women).	CT (Venous phase)	Support vector machine (SVM)	Accuracy 92.2%; AUC 0.98
Javed et al., 2022	Risk prediction of pancreatic cancer using AI analysis of pancreatic subregions in computed tomography images	To predict PDAC risk by automatically classifying CT scans into healthy control (low-risk) and prediagnostic (high-risk) groups and identifying pancreatic subregions likely to develop tumors.	108 CT scans from 72 subjects; internal dataset (66 scans) and external dataset (42 scans).	CT (Venous phase)	Naïve Bayes (NB), recursive feature elimination	Accuracy ~89.3%; Sensitivity 86%; Specificity 93%
Gotta et al., 2024	Unmasking pancreatic cancer: Advanced biomedical imaging for its detection in native versus arterial dual-energy computed tomography (DECT) scans	To investigate the potential of a machine-learning classifier using DECT radiomics to differentiate malignant pancreatic lesions from normal pancreatic tissue.	60 PC,40 normal.	DECT (Non-contrast and arterial phases)	Gradient-boosted trees (GBTs)	Non-contrast vs arterial phase: Accuracy 0.88 vs 0.97; Sensitivity 0.96 vs 0.97; AUC 0.96 vs 0.97

2.1. Deep Learning-Based Automated Detection Framework for Pancreatic Cancer

In recent years, deep learning (DL)-based imaging AI has gradually shifted towards a "representation learning-driven" end-to-end modeling paradigm. Models such as CNNs and Vision Transformers can learn multi-scale features directly from CT, MRI, or Endoscopic Ultrasound (EUS) images. Furthermore, these models can execute tasks including pancreas localization, anatomy/lesion segmentation, candidate lesion detection, and benign-malignant differentiation within a unified framework, thereby constructing an automated diagnostic pipeline that aligns more closely with clinical workflows (Figure 1).

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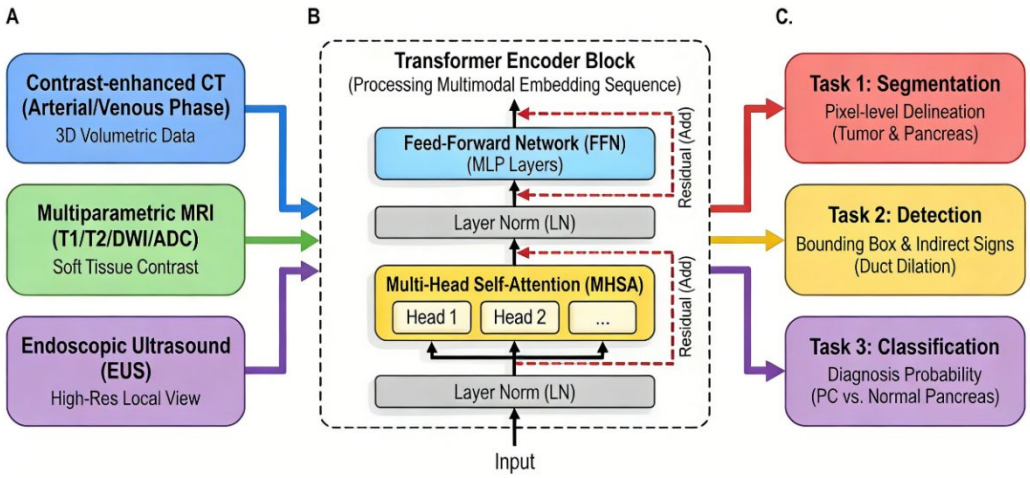

Figure 1: Deep learning architecture. A: The input of the raw data; B: The multimodal transformer encoder, and C represents the tasks that the model can perform.

In most studies, accurate segmentation of the pancreas and tumors is regarded as a fundamental step for subsequent detection and classification. Yang et al. [25] introduced the adaptive nnU-Net into the pancreatic cancer imaging processing workflow. By automatically configuring the network architecture and training strategy, they achieved three-dimensional segmentation of the pancreatic parenchyma and tumors. Their model attained a Dice Similarity Coefficient (DSC) of 0.764 on the test set, providing standardized input for volumetry and subsequent discrimination. To evaluate model stability in complex local environments, Kawamoto et al. [26] proposed a global-to-local evaluation strategy based on deep neural networks. This approach achieved DSC values of 87.4% and 85.5% for normal and abnormal pancreas segmentation, respectively, demonstrating that robust region of interest (ROI) extraction has a critical impact on binary classification performance under insufficient contrast conditions or complex background structures.

Aiming at diagnostic model construction and real-world tasks, Ma et al. [27] established a CNN classifier based on CT images in an early study, verifying the feasibility of deep learning in pancreatic cancer diagnosis. The model performed excellently across different phases, achieving the highest accuracy of 95.76% in the arterial phase, with accuracies of 95.47% and 95.15% in the plain scan and venous phases, respectively, laying the foundation for the development of automated systems. Addressing the screening scenario with extreme class imbalance (where "cancer" cases are far fewer than "normal" ones), Chen et al. [28] further constructed a population-based large-scale deep learning system. In a test involving nearly 1,500 subjects, the system achieved a sensitivity of 89.7% and a specificity of 92.8%. This study attempted to evaluate the model's detection capability for rare PC cases under a distribution close to the real world, providing a methodological reference for "reliable exclusion of normal pancreas" and "deployment evaluation in low-prevalence environments."

For small pancreatic cancers (diameter ≤ 2 cm), detection models relying solely on "mass visibility" are prone to limitations caused by low contrast or iso-density appearances. To improve sensitivity to atypical imaging manifestations, Ozawa et al. [17] proposed a dual-stream architecture that incorporates both solid lesion cues and secondary changes (e.g., main pancreatic duct dilation) into the discrimination process. By fusing these "direct signs" and "indirect signs," the model achieved a detection sensitivity of 96.0% for small pancreatic cancers, significantly reducing missed diagnoses caused by indistinct masses. Abi Nader et al. [29] developed an automated detection algorithm specifically for portal venous phase CT. By learning the relative vascular-pancreatic anatomical relationships and simultaneously modeling cues from pancreatic duct dilation and pancreatic lesions, this method achieved an area under curve (AUC) of 0.98 and a sensitivity of 94%, effectively reducing the false-positive risk of misidentifying normal anatomical structures as tiny tumors.

EUS offers high-resolution advantages in assessing pancreatic lesions; however, its diagnosis is highly dependent on operator experience and subjective judgment, leading to prominent consistency issues. Saraiva et al. [30] integrated EUS images from multi-center and multi-device sources to build a

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CNN model. Focusing on evaluating cross-domain generalization capabilities, their study indicated that acceptable discrimination performance could still be achieved under heterogeneous data source conditions, with identification accuracies of 99.1% for normal pancreas and 94.0% for pancreatic cancer. Tonozuka et al. [31] further conducted a pilot DL study on EUS-based pancreatic cancer detection, reporting an AUC of 0.94, highlighting the potential value of AI as a "second reader" in reducing inter-observer variability. To expand the discriminatory breadth of AI, Ni et al. [32] developed a CNN-based system capable of identifying not only pancreatic cancer but also neuroendocrine tumors and various other types of pancreatic lesions. In multi-class tasks, the system achieved an accuracy of 86.2% for pancreatic cancer identification. This capability holds significant clinical implications for excluding non-cancerous lesions and improving the overall specificity of diagnosis.

Beyond network architecture, imaging quality and reconstruction strategies directly influence the signal intensity and stability learnable by the model. Ichikawa et al. [33] evaluated the role of deep learning image reconstruction in 40-keV virtual monochromatic images. The study found that boundary distinguishability could be enhanced by reducing noise and improving contrast, thereby improving the model's capture of features related to tumor contours and further optimizing boundary delineation capabilities in segmentation and detection.

2.2. Radiomics-Based Diagnostic Methods for Pancreatic Cancer

While deep learning has demonstrated outstanding performance in end-to-end modeling, its "black-box" decision-making nature often leads to interpretability challenges, which can hinder clinical understanding and the adoption of these models due to reliability concerns. In contrast, radiomics adheres to a "decomposable" traditional machine learning workflow. Based on precise segmentation and preprocessing, radiomics involves the extraction of definable and reproducible image features (e.g., shape, gray-level statistics, and texture matrix features) from medical images. Subsequently, feature selection and classifiers (such as Support Vector Machines, Random Forest, and Logistic Regression) are employed to differentiate between PC and normal pancreas. The advantages of the radiomics paradigm include a transparent analysis pipeline and relatively explicit feature semantics, which facilitate stability analysis and cross-center reproducibility assessments. Furthermore, radiomics makes it feasible to expand the research focus from "visible masses" to the "whole pancreas background" and the pre-diagnostic occult stage, offering methodological avenues for quantifying early risk signals (Figure 2).

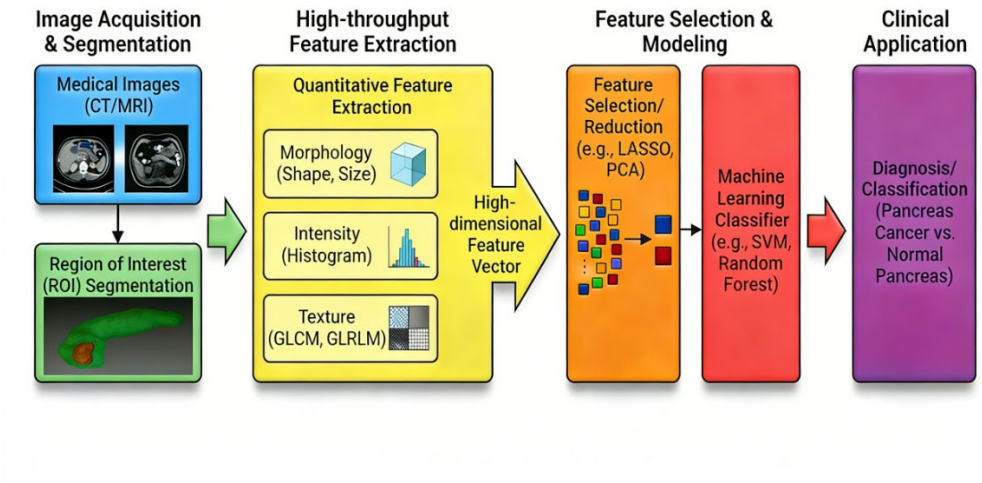

Figure 2: Radiomics Workflow.

The core premise of radiomics is that histological alterations within the tumor and its microenvironment (e.g., fibrosis, variations in cell density, and microvascular perfusion) manifest as systematic changes in pixel distribution and texture statistics on the imaging level, which are often indiscernible to the naked eye. Based on this rationale, Chen et al. [34] proposed in a cross-regional multi-center cohort study that texture-related radiomic features extracted from conventional CT can distinguish PC from normal pancreas. Achieving a sensitivity of 94.7% and a specificity of 95.4%, their model maintained consistent diagnostic trends across different population sources. This suggests that even in scenarios lacking typical morphological signs, quantitative texture analysis may capture "sub-visual"

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structural disruptions, providing supplementary evidence for early diagnosis.

In terms of modeling strategies, the focus of previous studies has shifted from "local lesion-ROI" centered feature extraction to "whole pancreas-organ level" characterization. Chu et al. [35] extracted 478 phenotypic features from the whole pancreatic volume and utilized a Random Forest classifier for dimensionality reduction analysis. They found that specific combinations of texture and shape features could complete the binary classification task with extremely high accuracy (AUC 99.9%). This result powerfully demonstrates that quantitative mathematical features can surpass the visual perception of radiologists, delineating precise digital boundaries between "normal" and "malignant" tissues. To further refine diagnostic granularity, Ren et al. [36] developed a CT-based radiomics diagnostic method aimed not only at differentiating benign from malignant cases but also at distinguishing early-stage from advanced PC. Their Random Forest model achieved an accuracy of 97.7%, a sensitivity of 97.6%, and a specificity of 97.8%, proving the dynamic evolutionary patterns of radiomic features consistent with tumor staging.

Traditional diagnostic imaging often focuses on visible masses, with insufficient attention paid to diffuse changes in the pancreatic background parenchyma. Based on the concept of the "field effect"—where carcinogenic factors may induce subtle structural and textural changes throughout the organ prior to mass formation—Wang et al. [37] proposed a whole-pancreas radiomics modeling framework. Instead of being confined to the tumor region, this approach constructs an organ-level "radiomic fingerprint" and screens for more robust features through uncertainty analysis. The model achieved excellent performance in an independent test set, with an AUC of 0.910 and an accuracy of 93.5%, indicating that the pancreatic parenchyma in PC patients may exhibit texture patterns distinct from healthy controls even in non-mass regions. Javed et al. [38] further focused on pancreatic sub-regions, utilizing AI to analyze texture features in the head, body, and tail of the pancreas for risk prediction. With a prediction accuracy of 88.2% (sensitivity 82.5%, specificity 94.0%), their study revealed that occult signals suggestive of carcinogenesis might exist even in unaffected sub-regions. The value of such studies lies in elevating "normal pancreas modeling" from a passive control to an active subject of characterization, providing potential pathways for screening or risk stratification.

Evidence with even greater clinical translational significance comes from the retrospective analysis of "pre-diagnostic imaging." Mukherjee et al. [39] trained radiomics machine learning models using CT images obtained 3 to 36 months prior to the clinical diagnosis of PC patients. The study showed that the model could identify imaging patterns associated with subsequent PC occurrence. The SVM classifier achieved high performance (AUC 0.98, sensitivity 95.5%, specificity 90.3%). This establishes the potential of radiomics as a "time machine," enabling ultra-early intervention by identifying occult microscopic textural anomalies before macroscopically visible pathological changes occur.

To overcome the limitations of single modalities, the combination of multi-parametric imaging and radiomics has become a new trend. Koch et al. [40] integrated Dual-Energy CT (DE-CT), Diffusion-weighted MRI (DWI), and radiomic features to construct a multi-parametric detection and prognosis prediction model. Achieving an AUC of 0.995, this confirmed the critical role of complementary multi-modal information in enhancing diagnostic efficacy. Similarly utilizing DECT technology, Gotta et al. [41] employed advanced biomedical imaging analysis methods aimed at "revealing" pancreatic cancer lesions that are difficult to detect on conventional images using material decomposition maps. Their two developed DECT models achieved AUCs of 0.97 and 0.96, respectively, providing richer qualitative and quantitative inputs for radiomics analysis.

In the development of PC-aided diagnostic tools, Chang et al. [42] developed a computer-aided detection tool combining 2D and 3D radiomics and tested it on population data that more closely reflected the real world. The tool achieved robust results in distinguishing PC from non-PC cases (AUC 0.947, sensitivity 91.8%, specificity 82.2%). The study highlighted the advantage of 3D features in capturing tumor spatial heterogeneity and confirmed that multi-dimensional radiomics models can maintain robust detection rates and effectively reduce false-positive risks even in real-world screening scenarios with extreme sample imbalance.

Despite the promising prospects of radiomics, its sensitivity to image acquisition parameters (e.g., scanner model, slice thickness, noise levels) remains a major barrier to clinical translation. To address this, Mukherjee et al. [43] proposed a stress-testing evaluation strategy based on image perturbation. By simulating conditions such as noise, rotation, and resolution changes, they screened for interference-resistant features and more robust model configurations, providing a methodological reference for building generalizable systems. Meanwhile, feature consistency across different software platforms is another issue that multi-center studies must face. Chu et al. [44] compared commercial software with in-house developed software regarding feature extraction and model performance. They pointed out that

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despite systematic biases, comparable diagnostic performance could still be obtained through strict standardization and calibration. This finding emphasizes the importance of establishing cross-platform feature standardization protocols for multi-center research.

3. Discussion

AI technologies are reshaping the diagnostic pathways for PC. Deep learning-based image analysis frameworks have gradually established a realistic foundation for conducting large-scale opportunistic screening at the population level. Studies exemplified by end-to-end models such as "PANDA" [45] demonstrate that AI can achieve high-throughput, automated triage and flagging within highly heterogeneous real-world clinical settings. In particular, through the comprehensive integration of indirect signs such as main pancreatic duct dilation, AI has significantly improved the detection sensitivity for small pancreatic cancers (diameter ≤ 2 cm) to 85.7%. This, to a certain extent, mitigates the risk of missed diagnoses by radiologists working under conditions of high workload and visual fatigue. Distinct from deep learning, which emphasizes automation and representation learning, radiomics offers an irreplaceable quantitative avenue for revealing tumor microenvironment heterogeneity. Although radiomics relies on image preprocessing, feature extraction, and dimensionality reduction—lacking the automation advantages of end-to-end models—it benefits from the traceable definitions of texture, shape, and statistical features, as well as low computational resource requirements. Consequently, radiomics is capable of capturing "sub-visual" textural alterations that are indiscernible to the naked eye. Particularly in the holistic phenotypic analysis of the "whole pancreas" background and retrospective studies of pre-diagnostic imaging, radiomics has successfully constructed risk prediction models that precede overt morphological changes, providing a potential imaging basis and stratification tools for "ultra-early" intervention.

Although AI has repeatedly demonstrated diagnostic performance approaching or even exceeding that of human experts in experimental settings [46-52], its real-world translation into routine clinical practice remains limited. The transition from "algorithmic performance" to "clinical tools" is constrained by a confluence of factors involving data, workflows, and governance. The primary challenge lies in interpretability and trust. Leveraging powerful feature learning capabilities, deep learning models can execute automated workflows from segmentation to classification with minimal manual intervention, laying the foundation for efficiency enhancement. However, their "black-box" nature remains a central barrier to clinical adoption: although visualization methods such as heatmaps can reveal the model's attentional regions, these explanations often remain at the correlation level and struggle to correspond to specific biological mechanisms, thereby limiting their credibility and accountability in high-risk decision-making. In contrast, radiomics, grounded in computable and reproducible quantitative features, can map imaging phenotypic differences associated with stromal reactions and microvascular distribution, offering an inherently stronger framework for biological interpretability. The second challenge concerns generalization and domain shift. Current high-performance results are often predicated on training data from single centers or specific populations. Performance often suffers from varying degrees of degradation when models encounter variations in cross-institutional CT scanner parameters (e.g., tube voltage, slice thickness, reconstruction algorithms) and contrast agent injection protocols. Notably, the sensitivity of radiomic features to acquisition and reconstruction parameters is particularly pronounced, making cross-center and cross-device feature standardization and robustness assessment critical prerequisites for clinical translation.

Future research should systematically evaluate the real-world efficacy and safety boundaries of algorithms through prospective clinical trials across multiple centers, devices, and populations. Furthermore, integrating multi-modal data is essential to enhance the model's coverage of diverse clinical pathways for various diseases. On the other hand, image enhancement and domain consistency methods incorporating physical constraints and verifiable mechanisms should be explored. These approaches aim to mitigate domain shifts caused by discrepancies in scanning protocols, reconstruction algorithms, and contrast schemes, thereby fundamentally improving model robustness and reproducibility. With the progressive refinement of standardized workflows, interpretability, and accountability mechanisms, alongside the continuous establishment of clinical trust in real-world applications, AI is poised to be embedded into the radiological workflow as a "second pair of eyes." By optimizing resource allocation while enhancing early detection rates, AI will provide sustainable technical support to transform the clinical predicament of pancreatic cancer being "diagnosed at a late stage," ultimately promising substantive improvements in patient survival outcomes.

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4. Conclusion

In the diagnosis of pancreatic cancer versus normal pancreas, both deep learning and radiomics have exhibited exceptional diagnostic efficacy, with accuracy ranges of 86.2%–95.8% and 88%–99.2%, respectively. However, the translation from "algorithmic models" to "clinical tools" still faces significant challenges. The primary obstacle is the substantial heterogeneity of imaging data resulting from the lack of unified standards for scanning protocols, equipment parameters, and reconstruction algorithms. Future research should focus on multi-center prospective studies to construct intelligent diagnostic systems that are high-performing, robust, and interpretable, while seamlessly integrating with clinical workflows. Furthermore, close collaboration with physicians during system development is essential to continuously enhance model performance and interpretability through feedback and resolution mechanisms derived from practical application.

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