Scientific Research Publishing

Open Journal of Gastroenterology, 2025, 15(4), 148-157
https://www.scirp.org/journal/ojgas
ISSN Online: 2163-9469
ISSN Print: 2163-9450

The Role of Artificial Intelligence in Pancreatic Cancer Detection: A Systematic Review

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How to cite this paper: Ethakota, J., Singh, B., Bai, S., Tareen, H., Kumar, D. and Malik, D.B. (2025) The Role of Artificial Intelligence in Pancreatic Cancer Detection: A Systematic Review. *Open Journal of Gastroenterology*, **15**, 148-157.
https://doi.org/10.4236/ojgas.2025.154015

Received: March 14, 2025
Accepted: April 15, 2025
Published: April 18, 2025

Abstract

Background: Pancreatic cancer is the fourth leading cause of cancer deaths in the United States, and early detection remains a significant challenge. Screening the general population is not feasible, but the rise of artificial intelligence (AI) has introduced new possibilities for improving early diagnosis and patient outcomes. Methods: A systematic literature search was conducted using PubMed, Google Scholar, and MEDLINE using MeSH terms "Artificial intelligence or AI", and "diagnosis" and "pancreatic carcinoma or pancreatic adenocarcinoma". Prisma guidelines were adhered to, and a total of 47 studies resulted, 10 articles were duplicates, 11 articles were excluded as they did not align with the topic, 7 articles could not be retrieved, 13 articles were excluded as they did not fit the criteria, 6 retrospective studies are included in this study. The inclusion criteria for this study are AI being used in the diagnosis, only in pancreatic cancer, within the last 5 years, only in English, and only retrospective studies were included. Results: One study used Digital Imaging Processing (DIP) for analyzing Endoscopic ultrasound (EUS) images from 153 pancreatic cancer patients, yielding a sensitivity of 97.98% and a specificity of 94.32%. Two studies explored Computer Aided Diagnosis (CAD) models applied to PET/CT and EUS images, achieving a sensitivity of 95.23% and specificity of 97.51% in PET/CT scans and 83.3% and 93.3% in EUS images, respectively. Another study used a Faster R-CNN model to analyze CT images from 338 pancreatic cancer patients showed high diagnostic accuracy in much less time. Additionally, two studies utilized Natural Language Processing (NLP) for identifying family histories of pancreatic cancer and detecting pancreatic cysts, with the latter achieving sensitivity and specificity rates of 99.9% and 98.8%. Conclusions: The current strategies for early diagnosis of pancreatic cancer focus on serum biomarkers and EUS-guided Fine Needle Aspiration (EUS-FNA). Sensitivity varies and depends on the physician's expertise. AI is showing promise in improving pancreatic cancer diagnosis by enhancing early

detection and accuracy. Techniques like deep learning, NLP-based models, Faster R-CNN, and CAD systems analyze medical data and images more effectively than manual methods. AI holds the potential to shape the future of pancreatic cancer diagnosis and improve patient outcomes.

Keywords

Pancreatic Cancer, Artificial Intelligence, Detection, Endoscopic Ultrasound, Pet Scan, CT Scan

1. Introduction

Pancreatic cancer is an aggressive malignancy of the digestive system, has rapid progression, early metastasis, high mortality, and poor prognosis, so it is considered as the "king of cancer" [1]. There are several risk factors such as obesity, smoking, and alcohol intake, but the exact etiology is unknown. Screening the general population for early identification of pancreatic cancer is infeasible, and there is no reliable test for its early detection. Screening high-risk populations might be effective in reducing mortality, about 10% of them have a familial basis [2]. It is the fourth leading cause of cancer mortality in the United States. According to Cancer Statistics 2021, the American Cancer Society reported approximately 60430 new cases and 48220 deaths for pancreatic cancer in the United States, ranking third after lung and bronchus cancer and colorectal cancer [3]. Positron Emission Tomography/Computed Tomography (PET/CT), which could be used to obtain both CT and PET sequential images at the same session, plays an important role in pancreas cancer diagnosis [4]. Endoscopic ultrasound (EUS) is a more accurate imaging procedure compared with other imaging methods in the diagnosis and staging of pancreatic tumors [5] [6]. The combination of EUS and EUS-guided FNA (EUS-FNA) in patients with pancreatic disease can make an accurate diagnosis of pancreatic cancer in addition to providing precise staging information [7]-[9]. Therefore, early diagnosis and accurate staging before surgery are key to improving the cure rate and prognosis [10]. Recently, the advent of artificial intelligence (AI) has introduced promising new possibilities for improving the diagnosis of pancreatic cancer. AI, particularly with deep learning algorithms, Natural Language Processing (NLP)-based, Faster R-CNN deep neural network, digital imaging processing (DIP) technique, computer aided diagnosis (CAD) has demonstrated potential in analyzing complex medical data, identifying subtle patterns, and enhancing the accuracy and speed of cancer detection. Machine learning is a type of AI capable of analyzing behavior using algorithms fed and trained by a large amount of data [11]. Deep learning is based on several layers of neural networks which combine different algorithms inspired by the human brain [12]. Artificial neural networks (ANN) are algorithmic imitations of the human brain, they receive input, process through a series of operations and produce an output [13]. This systematic review aims to review the existing literature re-

garding the role of AI in the diagnosis of pancreatic carcinoma, explore the current applications and potential of AI in the diagnosis of pancreatic cancer, discussing its benefits, challenges, and implications for clinical practice.

2. Materials and Methods

A systematic literature search was conducted for studies using AI in pancreatic cancer detection, using PubMed, Google Scholar, and MEDLINE using MeSH terms "Artificial intelligence or AI", and "diagnosis" and "pancreatic carcinoma or pancreatic adenocarcinoma". Prisma guidelines were adhered to, and a total of 47 studies resulted, 10 articles were duplicates, 11 articles were excluded as they did not match with the topic, 7 articles could not be retrieved, 13 articles were excluded as they did not fit the criteria and 6 retrospective studies are included in this study (See Figure 1).

The inclusion criteria for this study are AI being used in the diagnosis, only in pancreatic cancer, within the last 5 years, only in English, and only retrospective studies were included.

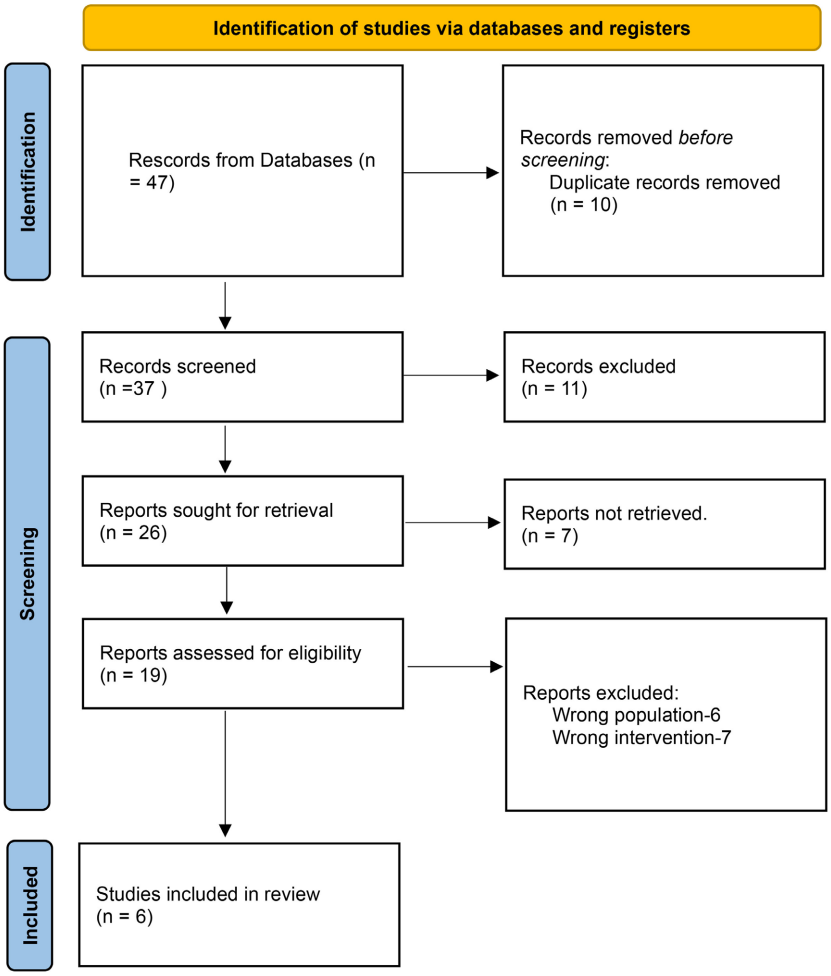

Figure 1. PRISMA (preferred reporting items for systemic reviews and metanalysis) flow chart.

3. Results and Discussion

Current strategies for early diagnosis of pancreatic cancer are mainly based on serum biomarkers, commonly used biomarkers is serum carbohydrate antigen 19-9 (CA19-9). As a screening tool it's use is suboptimal because of its low sensitivity (median 79%, range 70% - 90%) and specificity (median 82%, range 68% - 91%) [14]. The diagnosis of pancreatic cancer remains a great challenge especially in populations with chronic pancreatitis. Published studies reported that even with the application of EUS-FNA, the sensitivity in diagnosing pancreatic cancer varies from 80% to 90% [7] [9] [15] [16]. When there is coexistence of chronic pancreatitis and pseudo tumoral pancreatitis, the sensitivity may decrease to less than 75% (it has even been as low as 54% in some studies) [17]. Interpretation of EUS images is subjective and reliability of a diagnosis depends on the physicians' experience which limits the accuracy of the diagnostic results [18].

Therefore, the development of an accurate imaging processing technique that requires less manual intervention is important. The development of artificial intelligence in image processing has given the opportunity of application to the medical field, creating a new era of digital medicine [19]. The use of artificial intelligence to process CT images and track and identify diseased tissue could substantially reduce manual operations, significantly increase the processing speed and produce consistent and highly accurate results that are convenient for integration and large-scale applications.

Currently, automatic artificial intelligence (AI) identification of medical images is focused on lesion identification, labeling, and three-dimensional (3D) reconstruction of the target region. These processes all use deep learning to learn knowledge and build networks from a large number of medical images. Consequently, AI can diagnose specific lesions and has greater accuracy than highly experienced physicians in diagnosing lung, skin, prostate, breast, and esophageal cancers based on image recognition [20]-[24].

Even though the diagnostic accuracy of deep learning platforms is better, this research aims to develop an assistive tool to aid radiologists in making effective and accurate diagnoses, but not as a substitute for doctors [25]. With the advent of AI, the accuracy, sensitivity and specificity of pancreatic cancer diagnosis has shown an improvement. This systematic review includes six retrospective studies that showcased the use of AI in pancreatic cancer detection (See **Table 1**).

Table 1. Baseline Study characteristics.

Study	Sample size	Imaging/ diagnostic modality	AI technique	Specificity (%)	Sensitivity (%)	Limitations
Zhang *et al.* [14]	153	Endoscopic ultrasound	Digital imaging processing (DIP)	94.32	97.98	Small sample size, Support vector machine (SVM) not performed in real time

Continued

Roch *et al.* [26]	50 669	CT scan	Automated natural language processing (NLP)	98.80%	99.90%	Pilot study conducted at a single institution
Mehrabi *et al.* [27]	Not Specified	EMR-text-based analysis	Natural language processing (NLP)	Not specified	Not specified	Performed at only 2 institutions, room for improvement in distinguishing relationships accurately
Ozkan *et al.* [28]	202	Endoscopic ultrasound	Computer-aided diagnosis (CAD) system	93.3	83.3	Small sample size, single-center and single-equipment study
Li *et al.* [29]	80	PET/CT	Computer-aided diagnosis (CAD) system	97.51	95.23	Small sample size
Liu *et al.* [30]	338	Sequential contrast enhanced CT	Faster region-based convolution network (Faster R-CNN) model	Not specified	Not specified	Single center study

Zhang *et al.* (2010), performed a retrospective, controlled, single-center study which demonstrated the potential of AI-driven digital imaging processing (DIP) in enhancing endoscopic ultrasound (EUS) for pancreatic cancer detection. Endoscopic ultrasound images (EUS) of 153 pancreatic cancer patients diagnosed in a hospital for a period of 33 months were taken for digital image processing on a support vector machine. The results of the study revealed a sensitivity of 97.98 %, specificity of 94.32%, positive predictive value of 99.45%, negative predictive value of 98.65% and accuracy of 97.77% [14]. These results highlighted AI's ability to standardize image interpretation and reduce diagnostic variability, which is critical given the subtle morphological features of early pancreatic malignancies. However, the study's reliance on a support vector machine (SVM) model and its small sample size ($n = 153$) raised concerns about generalizability.

Roch *et al.* (2014) they performed a single-institution prospective pilot study to identify at risk of pancreatic cancer. The multidisciplinary team developed NLP-based algorithms designed to identify pancreatic cysts in unstructured CT reports. These algorithms were built using keywords frequently used by physicians and were programmed to automatically scan electronic medical records. Those with pancreatic cysts/ductal dilatation were identified using 566233 CT images of 50669 patients who have undergone CT for various causes in a 7-month period, 623 positive patients with pancreatic cysts were identified. It was manually validated by experts in pancreatology, and 615 patients were identified by manual experts. They achieved exceptional performance with a sensitivity of 99.9%, specificity of 98.8% [26]. This approach addressed the challenge of incidental cyst

identification in large-scale electronic medical records (EMRs), which offered a scalable solution for early risk stratification. However, as a single-institution pilot study (n = 50,669 reports), its findings may be influenced by institutional biases in radiology reporting terminology.

Mehrabi *et al.* (2015) conducted a retrospective observational study with a natural language processing (NLP) methodology applied to clinical records. It involved analyzing existing electronic medical records (EMRs) from two institutions (Indiana University and Mayo Clinic) to extract family history data related to pancreatic cancer. NLP system identification of at risk patients with family history of pancreatic cancer as there is increased risk of 10% in those with family history, 7 to 9 fold increase in incidence of pancreatic cancer when there is one first degree relative, more if it was below 30 years of age and increasing to 17 - 32 fold if three or more first degree relatives with cancer [27]. The study was done in 3573 pancreatic cancer patients of which 2923 were found to have family history and in 7270 patients with any cancer in 10 months with 80000 to 95000 reports, 60% were used for training and 40% for testing. The recall was 91.6%, precision 75.3%, negation detection was 99.1% although there were errors in sentence detection in complicated family relations [27]. The NLP system demonstrated consistent performance across both institutes, with a high inter-annotator agreement of 95.9% and accurate identification of pancreatic cancer family history. While the study's dual-institution design improves generalizability compared to single-center efforts, its inability to distinguish nuanced clinical relationships (e.g., differentiating benign cysts from premalignant lesions) highlights its limitations.

Ozkan *et al.* (2016) performed a retrospective study that evaluated the performance of a computer-aided diagnosis (CAD) system in detecting pancreatic cancer using endoscopic ultrasound (EUS) images of different age groups as outline, borders and echogenicity of pancreas change as the age progresses. The classification was age less than 40 years, 40-60 years, greater than 60 years. Accordingly, nine months EUS images were processed for CAD for better pattern recognition based on 20 reliable features processed in artificial neural network (ANN). Around 60 images of 40 patients below 40 years (11 with cancer 29 non cancer), 73 images of 58 cases in the age group of 40-60 years (36 with cancer and 22 non cancer), 189 images of 74 cases in the age group > 60 years (46 with cancer and 28 non cancer) were processed. The higher number of cancer patients in the older age group shows the raised incidence as the age progresses. Later images from 202 pancreatic cancer patients and 130 non-cancer patients were tested. 200 random tests were done, the accuracy was 92%, 88.5%, 91.7% in the three age groups respectively. Sensitivity was 87.5%, 85.7%, 93.3% and specificity was 94.1%, 91.7% and 88.9% in the respective age groups. Overall average accuracy when all three age groups combined was 87.5%, sensitivity 83.3%, specificity was 93.3% [28]. In contrast to assessment using EUS images in general, this age differentiation showed better performance in diagnosing pancreatic cancer accurately. They achieved a specificity of 93.3% but a lower sensitivity of 83.3% [28]. This disparity

suggested the model may prioritize minimizing false positives at the expense of missing true positives, a significant concern for pancreatic cancer given its aggressive progression. The study's small sample size (n = 202) and reliance on single-center, single-equipment data further limit translational relevance.

Li *et al.* (2018) performed a retrospective observational study with a focus on medical image analysis and machine learning. They utilized a computer aided diagnosis (CAD) system for PET/CT imaging, reporting high specificity (97.51%) and sensitivity (95.23%), which demonstrated AI's ability to leverage metabolic and anatomical data for precise lesion characterization [29]. This consists of pancreatic segmentation pseudocolor images that are obtained by gray interval mapping (GIP) by using simple linear iterative clustering (SLIC), principal feature along with some non principal features extraction and selection by using dual threshold principal component analysis (DTPCA) and finally using Hybrid feedback –support vector machine-random forest constructed by 8 types of SVM in 3 separate hyperplanes and 5 SVM kernels to diagnose pancreatic cancer. 80 case images were assessed with accuracy of identification 96.47%, sensibility 95.23%, sensitivity of 97.5% [29]. Later 3D CT scan images from public data were assessed. This was found to be most efficient than other conventional methods. However, the small cohort (n = 80) restricted statistical power, and the lack of external validation raised concerns about whether the findings would apply to a broader population.

Liu *et al.* (2019) performed a retrospective observational study in which they employed a faster region-based convolution network (Faster R-CNN) model to analyze sequential contrast-enhanced CT scans. 238 pancreatic patient's sequential CT images were processed in Faster region based convolutional neural network (Faster R CNN) which was already trained. This Faster R CNN has a feature extraction network, a regional proposal network and regression network. Then clinical verification with 1699 images from 100 pancreatic cancer patients were verified. It showed an mean average precision of 0.7664 and the area under the receiver operating characteristic curve with trapezoid rule is 0.9632. (>0.9 is higher accuracy). Along with this accuracy it proved to be faster taking about 0.2 sec to process one CT image with an average of 3 secs for a patient with 15 CT images in contrast to 8 mins taken for manual reading [30]. So with usage of AI they were able to get accurate and faster diagnosis of pancreatic cancer by processing the contrast enhanced sequential CT images. Though specificity and sensitivity metrics were unreported, the Faster R-CNN AI system proved to be an effective, objective, and highly accurate method for diagnosing pancreatic cancer, offering a faster alternative to manual diagnosis. While deep learning architectures like Faster R-CNN hold promise for detecting temporal changes in cyst morphology, the study's single-center design (n = 338) and absence of performance benchmarks limited interpretability.

Even though AI has proven to be helpful in detection of pancreatic carcinoma, it has limitations, AI models require large, high-quality datasets to achieve accurate results. The variability in data quality across institutions can limit the effectiveness

of AI algorithms. AI models, especially deep learning algorithms, give us limited insights into their decision-making processes. Enhancing the interpretability of these models is crucial for gaining clinician trust and facilitating their integration into clinical practice. The use of AI in healthcare raises regulatory and ethical concerns, including data privacy, algorithmic bias, and the need for rigorous validation before clinical deployment. Addressing these issues is essential for the safe use of AI.

In our opinion, the CAD and DIP technique analyzing the PET/CT and EUS images was better than NLP techniques. The NLP technique had limitations interpreting the complicated relations and was also based on EMR interpretation whereas the CAD, DIP system analyzed the images, the CAD technique yielded higher sensitivity and specificity than DIP technique. The CAD and DIP technique did have limitations like interpretability and generalizability. Even though most of the studies were single center studies, the different AI techniques show the future of AI in pancreatic cancer detection. The ability to detect pancreatic cancer at an early stage requires advanced imaging techniques along with the development of newer AI techniques.

4. Conclusion

Although the incidence of pancreatic cancer is less, the mortality rate is high, and early diagnosis plays an important role in the prognosis. So, the importance of recognition of at-risk population will enable the primary physician for close follow up, leading to early intervention, which was enabled by natural language processing of data. Analyzing the EUS, the CT/PET images by CAD and Faster R-CNN, yielded higher accuracy, precision, with higher sensitivity, specificity and in lesser time than manual diagnosis. Usage of AI in pancreatic cancer makes an inexpensive, feasible, portable alternative where customization can be done depending on the need of the institution. In the future, the role of AI in pancreatic cancer diagnosis will lie in the development of more sophisticated models, the integration of multi-modal data, and the establishment of collaborative frameworks for data sharing and model validation. Further research is required on the usage of AI in detection and management in the field of oncology.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Siegel, R.L., Miller, K.D. and Jemal, A. (2018) Cancer Statistics, 2018. *CA*: *A Cancer Journal for Clinicians*, **68**, 7-30. https://doi.org/10.3322/caac.21442

[2] Permuth-Wey, J. and Egan, K.M. (2008) Family History Is a Significant Risk Factor for Pancreatic Cancer: Results from a Systematic Review and Meta-Analysis. *Familial Cancer*, **8**, 109-117. https://doi.org/10.1007/s10689-008-9214-8

[3] Siegel, R.L., Miller, K.D., Fuchs, H.E. and Jemal, A. (2021) Cancer Statistics, 2021. *CA*: *A Cancer Journal for Clinicians*, **71**, 7-33. https://doi.org/10.3322/caac.21654

[4] Wang, X. (2014) Utility of PET/CT in Diagnosis, Staging, Assessment of Resectability and Metabolic Response of Pancreatic Cancer. *World Journal of Gastroenterology*, **20**, Article No. 15580. https://doi.org/10.3748/wjg.v20.i42.15580

[5] DeWitt, J., Devereaux, B., Chriswell, M., McGreevy, K., Howard, T., Imperiale, T.F., *et al.* (2004) Comparison of Endoscopic Ultrasonography and Multidetector Computed Tomography for Detecting and Staging Pancreatic Cancer. *Annals of Internal Medicine*, **141**, 753-763. https://doi.org/10.7326/0003-4819-141-10-200411160-00006

[6] Brand, B., Pfaff, T. and Binmoelle, K.F. (2000) Endoscopic Ultrasound for Differential Diagnosis of Focal Pancreatic Lesions, Confirmed by Surgery. *Scandinavian Journal of Gastroenterology*, **35**, 1221-1228. https://doi.org/10.1080/003655200750056736

[7] Mishra, G., Zhao, Y., Sweeney, J., Pineau, B.C., Case, D., Ho, C., *et al.* (2006) Determination of Qualitative Telomerase Activity as an Adjunct to the Diagnosis of Pancreatic Adenocarcinoma by Eus-Guided Fine-Needle Aspiration. *Gastrointestinal Endoscopy*, **63**, 648-654. https://doi.org/10.1016/j.gie.2005.11.056

[8] Eloubeidi, M.A., Chen, V.K., Eltoum, I.A., Jhala, D., Chhieng, D.C., Jhala, N., *et al.* (2003) Endoscopic Ultrasound-Guided Fine Needle Aspiration Biopsy of Patients with Suspected Pancreatic Cancer: Diagnostic Accuracy and Acute and 30-Day Complications. *American Journal of Gastroenterology*, **98**, 2663-2668. https://doi.org/10.1111/j.1572-0241.2003.08666.x

[9] Horwhat, J.D., Paulson, E.K., McGrath, K., Stanley Branch, M., Baillie, J., Tyler, D., *et al.* (2006) A Randomized Comparison of Eus-Guided FNA versus CT or Us-Guided FNA for the Evaluation of Pancreatic Mass Lesions. *Gastrointestinal Endoscopy*, **63**, 966-975. https://doi.org/10.1016/j.gie.2005.09.028

[10] McGuigan, A., Kelly, P., Turkington, R.C., Jones, C., Coleman, H.G. and McCain, R.S. (2018) Pancreatic Cancer: A Review of Clinical Diagnosis, Epidemiology, Treatment and Outcomes. *World Journal of Gastroenterology*, **24**, 4846-4861. https://doi.org/10.3748/wjg.v24.i43.4846

[11] Azencott, C.-A. (2022) Introduction au Machine Learning. 2nd Edition, Dunod, 272 p.

[12] Charniak, E. (2021) Introduction au Deep Learning. Dunod, 176 p.

[13] Sy, I., Bousso, M., Correa, A.I. and Dieng, M. (2023) State of the Art of Artificial Intelligence Applications in Oncology. *Open Journal of Applied Sciences*, **13**, 2245-2262. https://doi.org/10.4236/ojapps.2023.1312175

[14] Zhang, M., Yang, H., Jin, Z., Yu, J., Cai, Z. and Li, Z. (2010) Differential Diagnosis of Pancreatic Cancer from Normal Tissue with Digital Imaging Processing and Pattern Recognition Based on a Support Vector Machine of EUS Images. *Gastrointestinal Endoscopy*, **72**, 978-985. https://doi.org/10.1016/j.gie.2010.06.042

[15] Harewood, G.C. and Wiersema, M.J. (2002) Endosonography-Guided Fine Needle Aspiration Biopsy in the Evaluation of Pancreatic Masses. *The American Journal of Gastroenterology*, **97**, 1386-1391. https://doi.org/10.1111/j.1572-0241.2002.05777.x

[16] Agarwal, B., Abu-Hamda, E., Molke, K.L., Correa, A.M. and Ho, L. (2004) Endoscopic Ultrasound-Guided Fine Needle Aspiration and Multidetector Spiral CT in the Diagnosis of Pancreatic Cancer. *The American Journal of Gastroenterology*, **99**, 844-850. https://doi.org/10.1111/j.1572-0241.2004.04177.x

[17] Ardengh, J.C., Lopes, C.V., Campos, A.D., *et al.* (2007) Endoscopic Ultrasound and Fine Needle Aspiration in Chronic Pancreatitis: Differential Diagnosis between Pseudotumoral Masses and Pancreatic Cancer. *JOP*, **8**, 413-421.

[18] Du, T., Bill, K.A., Ford, J., Barawi, M., Hayward, R.D., Alame, A., *et al.* (2018) The

Diagnosis and Staging of Pancreatic Cancer: A Comparison of Endoscopic Ultrasound and Computed Tomography with Pancreas Protocol. *The American Journal of Surgery*, **215**, 472-475. https://doi.org/10.1016/j.amjsurg.2017.11.021

[19] Walczak, S. and Velanovich, V. (2017) An Evaluation of Artificial Neural Networks in Predicting Pancreatic Cancer Survival. *Journal of Gastrointestinal Surgery*, **21**, 1606-1612. https://doi.org/10.1007/s11605-017-3518-7

[20] Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M., *et al.* (2017) Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks. *Nature*, **542**, 115-118. https://doi.org/10.1038/nature21056

[21] Nakamura, K., Yoshida, H., Engelmann, R., MacMahon, H., Katsuragawa, S., Ishida, T., *et al.* (2000) Computerized Analysis of the Likelihood of Malignancy in Solitary Pulmonary Nodules with Use of Artificial Neural Networks. *Radiology*, **214**, 823-830. https://doi.org/10.1148/radiology.214.3.r00mr22823

[22] Chen, C., Chou, Y., Han, K., Hung, G., Tiu, C., Chiou, H., *et al.* (2003) Breast Lesions on Sonograms: Computer-Aided Diagnosis with Nearly Setting-Independent Features and Artificial Neural Networks. *Radiology*, **226**, 504-514. https://doi.org/10.1148/radiol.2262011843

[23] Hou, Q., Bing, Z., Hu, C., Li, M., Yang, K., Mo, Z., *et al.* (2018) Rankprod Combined with Genetic Algorithm Optimized Artificial Neural Network Establishes a Diagnostic and Prognostic Prediction Model That Revealed C1QTNF3 as a Biomarker for Prostate Cancer. *EBioMedicine*, **32**, 234-244. https://doi.org/10.1016/j.ebiom.2018.05.010

[24] Horie, Y., Yoshio, T., Aoyama, K., Yoshimizu, S., Horiuchi, Y., Ishiyama, A., *et al.* (2019) Diagnostic Outcomes of Esophageal Cancer by Artificial Intelligence Using Convolutional Neural Networks. *Gastrointestinal Endoscopy*, **89**, 25-32. https://doi.org/10.1016/j.gie.2018.07.037

[25] Lu, Y., Yu, Q., Gao, Y., Zhou, Y., Liu, G., Dong, Q., *et al.* (2018) Identification of Metastatic Lymph Nodes in MR Imaging with Faster Region-Based Convolutional Neural Networks. *Cancer Research*, **78**, 5135-5143. https://doi.org/10.1158/0008-5472.can-18-0494

[26] Roch, A.M., Mehrabi, S., Krishnan, A., Schmidt, H.E., Kesterson, J., Beesley, C., *et al.* (2015) Automated Pancreatic Cyst Screening Using Natural Language Processing: A New Tool in the Early Detection of Pancreatic Cancer. *HPB*, **17**, 447-453. https://doi.org/10.1111/hpb.12375

[27] Mehrabi, S., Krishnan, A., Roch, A.M., *et al.* (2015) Identification of Patients with Family History of Pancreatic Cancer—Investigation of an NLP System Portability. Studies in Health Technology and Informatics, Vol. 216, IOS Press, 604-608. https://doi.org/10.3233/978-1-61499-564-7-604

[28] Kurt, M., Ozkan, M., Cakiroglu, M., Kocaman, O., Yilmaz, B., Can, G., *et al.* (2016) Age-Based Computer-Aided Diagnosis Approach for Pancreatic Cancer on Endoscopic Ultrasound Images. *Endoscopic Ultrasound*, **5**, 101-107. https://doi.org/10.4103/2303-9027.180473

[29] Li, S., Jiang, H., Wang, Z., Zhang, G. and Yao, Y. (2018) An Effective Computer Aided Diagnosis Model for Pancreas Cancer on PET/CT Images. *Computer Methods and Programs in Biomedicine*, **165**, 205-214. https://doi.org/10.1016/j.cmpb.2018.09.001

[30] Liu, S., Li, S., Guo, Y., Zhou, Y., Zhang, Z., Li, S., *et al.* (2019) Establishment and Application of an Artificial Intelligence Diagnosis System for Pancreatic Cancer with a Faster Region-Based Convolutional Neural Network. *Chinese Medical Journal*, **132**, 2795-2803. https://doi.org/10.1097/cm9.0000000000000544