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REVIEW ARTICLE

Transfer Learning for Pancreatic Ductal Adenocarcinoma Detection: A Comprehensive Review

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ABSTRACT: Transfer learning has demonstrated significant potential within artificial intelligence, offering previously unrecognized advantages in medical imaging and cancer diagnosis. Transfer learning requires less data than traditional deep learning to develop models for new tasks. This review explores how transfer learning techniques can improve both the detection and diagnostic accuracy of pancreatic ductal adenocarcinoma (PDAC), a highly lethal and difficult-to-detect cancer. This review analyzes transfer learning applications to three key data types: computed tomography scans, ultrasound scans, and cell biopsies. While still a young field, early findings suggest that transfer learning improves diagnostic accuracy while reducing the need for data, making it an efficient alternative to traditional deep learning. Transfer learning achieved AUC scores comparable to deep learning and demonstrated higher accuracy than human professionals. However, there is still more to be done in this field, especially the need for further studies to validate transfer learning in PDAC detection. This research underscores the potential use of transfer learning in advancing more effective diagnostics for PDAC, which has significant potential to improve the current poor outcomes.

KEYWORDS: Computational Biology and Bioinformatics, Computational Oncology, PDAC, Transfer Learning, Deep Learning.

Introduction

Known as a "silent" disease, pancreatic cancer is difficult to detect early due to the absence of symptoms and the pancreas' hidden location among surrounding organs. This allows the disease to progress unchecked until it reaches an advanced stage. Once symptoms emerge, treatment efficacy is significantly reduced, and in many cases, the disease proves fatal. The early-stage detection of pancreatic cancer remains exceedingly uncommon, with only 9.7% of people diagnosed in its early stage.[1] By the time of detection in most individuals, pancreatic cancer has already metastasized, posing an even greater risk for patients. Pancreatic cancer is the fourth leading cause of cancer-related death within western societies and is projected to rise to the second leading cause by 2028.[1] Despite comprising only 3% of all cancers, it has a disproportionately high death rate with an annual death rate of 10.9 per 100,000.[1] Moreover, its survival rate has not improved over these past forty years unlike that of most other cancers.[1] There are many forms of pancreatic cancer, but this review is focused on Pancreatic Ductal Adenocarcinoma (PDAC), which forms when the exocrine duct cells that line the pancreas become cancerous and account for 90% of all cases of pancreatic cancer.[1]

There are several methods that clinicians currently use to detect PDAC, including Computed Tomography Scan (CT scan), Positron Emission Tomography Scan (PET Scan), Magnetic Resonance Imaging (MRI), Endoscopic Ultrasound (EUS), Ultrasound, and cell biopsy. Table 1 gives a brief description of the current methods used by doctors.

Table 1: Standard detection methods for PDAC. * This review analyzes these data types. This table emphasizes the strengths and limitations of current clinical PDAC detection methods and how they each work.

Detection Method	How does it work?	Pros	Cons
CT Scan*[2,3]	Computerized x-ray imaging, where a narrow beam of x-rays is aimed at a patient and quickly rotated to form cross-sectional images, which are stacked to form 3D images	Diagnose possibly fatal diseases, reduce the need for surgery, and check internal organs	Expensive, high energy use, low radiation exposure, contrast dye exposure, invasive
PET Scan[2,4]	A small dose of radioactive sugar is injected and collected by cells to image how organs and tissues are working	Diagnose possibly fatal diseases, reduce the need for surgery, and check internal organs	Expensive, high energy use, low radiation exposure, risk of allergic reaction to tracer, invasive
MRI[3,5]	Uses magnetic fields to provide a clear and detailed picture of an organ	Superior soft tissue imaging, radiation-free, and noninvasive.	Expensive, uses strong magnetic fields that are potential safety concerns
EUS*[3,6]	A thin, flexible tube called an endoscope is placed in the digestive tract, which releases ultrasound waves to create a detailed image of the digestive tract	Accurate diagnosis and the ability to collect tissue samples	Expensive, operator-dependent, risk of internal complications, limited availability, invasive
Ultrasound*[7]	A transducer is pressed against the area that is being studied, which sends and collects sound waves to map an image	Low-cost, noninvasive, fast, and effective for soft tissues	Cannot penetrate bone, air, or deep structures
Cell Biopsy*[8,9]	A doctor takes a small sample of cells from a region of your body through a needle or other instrument to analyze the cells, usually through a stain	Gold standard for diagnosis, staging tumors, and tracking treatment progress	Expensive, invasive, risk of internal complications, operator-dependent

Despite the existence of these methods shown in Table 1, the ability to detect PDAC remains an area of active investigation. In recent years, advancements in artificial intelligence (AI) have led to the development of new methods for detecting and analyzing not just pancreatic cancer but many types of cancer, with improved results in early detection. In recent years, the healthcare system has increasingly integrated technology,

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as evidenced by the FDA's approval of over 1,000 AI-assisted medical devices.[10] A notable example in cancer detection is a model trained on CT scans for lung cancer, which surpassed radiologists in accuracy. Additionally, the health company Optellum improved early detection by reducing false negatives in lung cancer screenings.[11] As of October 2023, there are 71 and counting AI-associated devices that have been documented and have already received FDA approval to be used in oncology-related fields.[12] Cancer radiology accounts for 54.8% of these devices, followed by pathology, which includes 19.7%, and radiation oncology with 8.5%.[12] The majority of these devices are created with machine learning, a key subfield of AI.

Machine learning has multiple subfields, including deep and transfer learning. Deep learning is the use of multi-layered artificial neural networks to learn from data by drawing patterns to form conclusions.[13] Machine learning was first used with cancer data in the early 2000s for cancer classification and subtype detection.[14] Since then, it has evolved into a more complex field that enables doctors to aid not only in cancer detection but in treatment as well. From drug-target identification through the analysis of genomic and epigenomic data to advanced methods for early cancer detection, deep learning integrates diverse medical data to provide a comprehensive understanding of cancer biology.[14] Deep learning in PDAC detection refers to the use of advanced neural networks, specifically identifying cells that may be cancerous in the pancreatic region. Deep learning is a key component in many of the studies examined in this review.

The focus of this review, however, is on the branch of machine learning called transfer learning. Transfer learning is a machine learning technique that leverages a pre-trained model, originally developed for one task or dataset, to improve performance on a different but related task or dataset.[15] By reusing learned features and knowledge, transfer learning accelerates training, enhances accuracy, and reduces the need for large labeled datasets. Due to its lower data requirements compared to traditional deep learning, transfer learning is particularly effective for developing models in underexplored areas. A notable limitation of transfer learning, however, is the assumption of similar features present in both the foundation model and the novel context, an assumption that doesn't always hold. Figure 1 shows a comparison between the architectures of deep learning and transfer learning. The classification layer in deep learning is trained from scratch using a large dataset, while in transfer learning, a pre-trained model is adapted with a new classification layer for a smaller dataset.

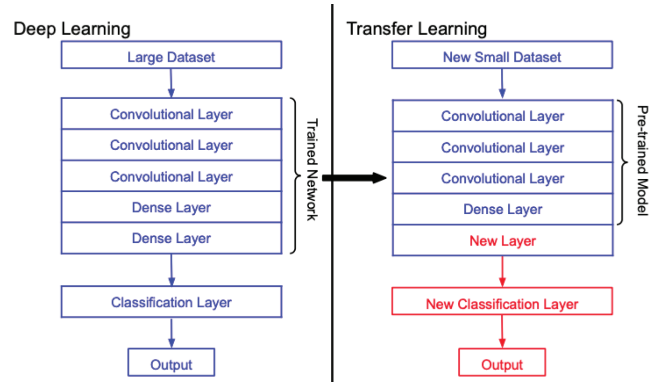

Figure 1: Deep learning vs transfer learning architecture. The left half represents a deep learning architecture, and the right half represents a transfer learning architecture. The blue portion indicates nodes of a deep learning model, and the red portion is the retrained elements (last layer of the deep learning model). Transfer learning usually borrows parameters from an existing model and trains only the last layer for a new task.

One of the first applications of transfer learning to cancer was with breast cancer imaging, which used a transfer learning model to help classify the different types of breast cancers.[16] Transfer learning is now widely used in tasks like image classification, including applications in ultrasound and CT imaging. Transfer learning is already applied to improve the accuracy of the diagnosis of lung cancer, helping classify Alzheimer's patients' severity based on MRI scans, and brain tumor segmentation.[17–19] In this review, we will highlight the way transfer learning is being applied to different data types, including CT scans, ultrasound, and cell biopsy, to compare the effectiveness of transfer learning to deep learning.

Table 2: Types of detection covered in the papers and their functions. This table outlines various AI-based diagnostic tasks, what they do, and an example of each.

Detection Type	Purpose	Example
Survival Analysis[20]	Predict patient prognosis like patient survival time or risk of disease progression	Use techniques like Cox Proportional Hazard Models
Classification[21]	Identify whether a given sample belongs to a particular category	Convoluted Neural Networks trained to label images as having PDAC or non-PDAC
Segmentation[21]	Delineate or outline specific regions of interest	U-Net architectures can help distinguish regions that may be cancerous
Feature Extraction[22]	Identify key characteristics or biomarkers from images that are relevant for diagnosis and prognosis	AI Models can extract information like cancer tumor size and shape

Researchers employ various methods to assess the performance of models, and the evaluation criteria can differ significantly across studies. Table 2 presents the types of analysis and detection discussed in this review, highlighting studies that vary in their use of transfer learning and deep learning techniques. In these studies, the commonly used metrics included accuracy, sensitivity, specificity, precision, F1 score, and index-based measurements. Table 3 presents a list of the important metrics and their interpretations.

Data Collection

We reviewed 28 research articles and selected 17 to use, all of which belonged to three major data types: CT, ultrasound, and cell biopsies. Data modalities were restricted to those described in Table 1 due to data abundance, along with alignment with gold-standard clinical practice criteria.[1] All sources were found on Google Scholar with the keywords we used below in Tables 4 and 5.

Table 3: List of metrics and what they measure. This summary highlights key evaluation metrics used to compare model effectiveness across studies.

Metric	Function	Pros	Cons
Area Under the Curve (AUC) / Area Under the Receiver Operating Characteristic Curve (AUROC)[23]	Evaluates classification models, particularly in binary classification tasks by measuring the ability of a model to distinguish between classes	Threshold-independent, less affected by class distribution	Hard to interpret in isolation
Concordance Index (C-Index)[24]	A measure of how well a model predicts the ranking of outcomes. Higher values indicate better prediction	Useful for survival analysis, less affected by class distribution	Complex interpretation, not suitable for discrete outcomes
Index of Prediction Accuracy (IPA)[25]	A general term for metrics that evaluate how well a model's predictions match actual results	Simple, intuitive, quick evaluation	Heavily affected by class distribution, doesn't capture the model's ability to distinguish between classes
Sensitivity (Recall)[23,26]	The ability of a test or model to correctly identify positive cases	Prioritizes true positives, useful for imbalanced data	Ignores false positives, which can lead to a high false positive rate
Specificity[26]	The ability of a test or model to correctly identify negative cases	Prioritizes true negatives, useful for avoiding false positives	Ignores false negatives, less useful in positive-detection tasks
Precision[23]	The proportion of true positive predictions out of all predicted positives	Focuses on the quality of positive predictions, good for imbalanced datasets	Ignores false negatives, not effective alone in imbalanced cases
F1 Score[23]	A measure of a model's balance between precision and sensitivity (recall), calculated as the harmonic mean of both	Balances precision and recall, useful for imbalanced datasets	Can mask trade-offs between precision and recall, which are less intuitive

Table 4: Data type frequency on Google Scholar without applying any time restriction. The search result data indicate that CT scans dominate PDAC-related research, reflecting their clinical importance and data availability.

Data Type	Results on Google Scholar with the keyword: PDAC + Data Type	Results on Google Scholar with the keyword: PDAC + "Transfer Learning" + Data Type	Results on Google Scholar with the keyword: PDAC + "Deep Learning" + Data Type
CT Scan	13,800 entries	286 entries	1,910 entries
Ultrasound	12,500 entries	168 entries	983 entries
Biopsy Samples	1,620 entries	27 entries	157 entries

When researching each of the three methods, we found that there were far more results for deep learning than for transfer learning. Additionally, it was easier to find previous research done on using transfer learning to analyze PDAC CT scans than ultrasound images. One reason is that CT scans are the most commonly used imaging method for patients with PDAC, providing a larger pool of available data. However, CT scans are often more challenging for humans to interpret, making them the most prominent application of transfer learning to achieve better outcomes. While cell biopsy is extensively researched, few studies apply it to transfer or deep learning, likely because it remains the gold standard for PDAC diagnosis. Transfer learning has been used less frequently for ultrasound data compared to other imaging modalities, as shown in Tables 4 and 5.

Table 5: Frequency of PDAC-related data types in scholarly literature on Google Scholar for both transfer and deep learning (2022–2025). These updated results from 2020–2025 show that transfer learning is still underutilized compared to deep learning in PDAC research.

Data Type	Results on Google Scholar with the keyword: PDAC + Data Type	Results on Google Scholar with the keyword: PDAC + "Transfer Learning" + Data Type	Results on Google Scholar with the keyword: PDAC + "Deep Learning" + Data Type
CT Scan	8,460 entries	234 entries	1,480 entries
Ultrasound	7,870 entries	130 entries	786 entries
Biopsy Samples	1,180 entries	16 entries	125 entries

Table 4 shows the number of entries that emerged on Google Scholar when we input a combination of keywords. For example, typing "PDAC + Transfer Learning + Ultrasound" gave 1490 results. Table 4 shows the total generated results. However, we focused our research on recent progress, so we further classified results within the past five years, 2020 to 2025. We acquired Table 5 the same way we did Table 4. However, it shows the number of entries that emerged on Google Scholar only from 2020 to the present and not all-time, like that of Table 4.

Tables 4 and 5 may give the false impression that substantial research has already been conducted on transfer learning, particularly in the field of PDAC, but that is not the case. Because Google Scholar parses keywords individually, search results often include studies unrelated to transfer learning or PDAC, or those that mention transfer learning without substantive analysis. Literature searches on Google Scholar yielded a greater number of deep learning studies related to PDAC across all three data types, compared to those involving transfer learning.

CT Scan

CT Scan Overview:

CT scans show a detailed image of the body, including bones, muscles, fat, organs, and blood vessels, and are often more detailed than X-ray images. This technology enables the combination of image slices into 3D models, allowing for better visualization of internal structures. This improves diagnostic accuracy and enhances surgical planning with precise anatomical representations. There are two main variants of CT scans: contrast versus non-contrast. Contrast CT scans are when a contrasting agent, typically iodine-based, is injected into a patient's bloodstream before scanning. The contrast agent contains a substance that can absorb the X-rays used in CT scans to make organs more visible on the computerized image. Due to the pancreas's location behind other organs, it needs contrast for doctors to study it. Non-contrast CT scans, on the other hand, use no agent. CT scans are one of the most common methods of PDAC detection, hence the large quantity of sources available. Large datasets containing many CT scans are often used to train transfer learning models. These datasets comprise images labeled to indicate the presence or

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absence of pancreatic tumors. Each image is associated with metadata detailing patient demographics and clinical information. The data is organized into training and validation sets to facilitate model development and assessment. Figure 2 illustrates the visual challenges of distinguishing PDAC from healthy pancreatic tissue. PDAC often appears similar to healthy tissue in CT imaging, making accurate diagnosis challenging due to subtle differences in texture and contrast, leading to potential false positives. The red regions in Figure 2 denote PDAC, while the yellow regions denote normal pancreatic tissue.

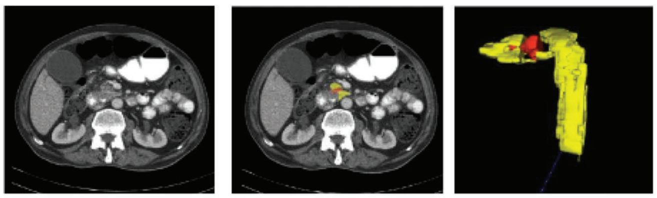

Figure 2: PDAC CT scan example. An abnormal pancreatic CT scan that illustrates the challenge of visually differentiating cancerous pancreatic regions from healthy tissue with the naked eye. This image is from Figure 1 of the study: Segmentation of PDAC and surrounding vessels in CT images using deep convolutional neural networks and texture descriptors.[27]

Studies:

The following 11 studies focused on the CT scan data type and whether it was transfer or deep learning. These are a representative sample, splitting the studies into five transfer learning-based and six deep learning-based studies. The transfer learning studies capitalize on pre-trained models to boost diagnostic accuracy and predictive performance, particularly in scenarios with limited data availability. These approaches underscore the efficacy of transfer learning in enhancing prognostic assessments, precise segmentation of medical images, and advancing early cancer detection. Conversely, deep learning studies deploy custom-built neural networks trained from scratch to discern patterns within extensive datasets. Both deep learning and transfer learning models have been utilized to analyze PDAC CT scans, exhibiting varying performance levels while highlighting substantial potential for future applications, such as the early prediction of PDAC.

Table 6: Summary of peer-reviewed studies employing CT scan data in PDAC research for transfer and deep learning-based approaches.

Study	Type of Learning	Data	Model	Performance	Key Takeaways
Zhang *et al.* 2020[28]	Transfer Learning	3 cohorts: 422 NSCLC patients, 68 PDAC patients, 30 independent PDAC patients	Convoluted Neural Network (CNN)-based survival model	Concordance index: 0.651 compared to 0.491 in radiomic-based models, Index of prediction accuracy: 11.81% compared to 3.80% in radiomic-based models	Outperformed radiomic-Cox models, effective in small PDAC cohorts
Zhang *et al.* 2021[29]	Transfer Learning	2 cohorts: 68 PDAC patients, 30 independent PDAC patients, 1428 radiometric images	CNN-based survival model	AUCs: 0.60 (PCA, Boruta), 0.55 (CPH), 0.50 (LASSO); Risk score-based method AUC: 0.84; High correlation coefficient >0.70	Transfer learning improves prognostic performance with limited data
Kothawade *et al.* 2024[30]	Transfer Learning	4080 labeled CT images, 3289 manually verified from Kaggle	Deep Learning CNN Transfer Learning YOLO	F1-score values of 1 and 0.99	Enhances tumor detection accuracy while reducing computational costs
Zhu *et al.* 2023[31]	Transfer Learning	104 PDAC patients, dual-phase imaging from Changhai Hospital of Naval Military Medical University	CycleGAN, U-Net	Dice: 81.57%, IoU: 71.35%, Sensitivity: 84.32%, Specificity: 99.86%	High segmentation accuracy, surpassing benchmarks in pancreatic imaging
Kim *et al.* 2024[32]	Transfer Learning	3058 CT reports from South Korea & USA	ClinicalBERT	Initial: C-index of 0.653 AUROC of 0.722 Trained on up to 15 consecutive reports: C-index of 0.811 AUROC of 0.888	Deep transfer learning improves survival prediction from CT reports
Chhikara *et al.* 2024[33]	Deep Learning	scRNA-seq data from 61 PDAC, 16 non-malignant pancreatic tissues (174,394 cells)	MobileNet	MobileNet + GMAp (LR = 0.001) achieved 98.16% accuracy, F1 score, and recall, with 98.17% precision. Accuracy improved by 3.66% over machine learning and 16.16% over deep learning 3-class classification.	Transfer learning improves early pancreatic cancer detection
Chen *et al.* 2023[34]	Deep Learning	1279 contrast-enhanced CT scans (546 pancreatic cancer, 733 controls)	Segmentation CNN	89.9% sensitivity and 95.9% specificity on an internal test set and 89.7% sensitivity and 92.8% specificity in real-world validation Sensitivity of 74.7% for tumors smaller than 2 cm	Effective pancreatic cancer detection, even for small tumors
Cao *et al.* 2023[35]	Deep Learning	3208 patients (training), 6239 (validation across 10 centers), 20,530 real-world cases	PANDA	AUC of 0.986-0.996 Identification and achieved 92.9% sensitivity and 99.9% specificity in real-world testing	Outperformed radiologists by 34.1% in sensitivity, 6.3% in specificity
Gandikota *et al.* 2023[36]	Deep Learning	500 samples (two classes)	W-Net + GhostNet + Deep Echo State Network	Accuracy: 96.98–99.02%, Precision: 97.18–99%	The TSADL-PCSC approach outperforms existing methods
Ramaekers *et al.* 2024[37]	Deep Learning	290 CT images (98 controls, 99 adenocarcinoma patients)	3D U-Net	Specificity: 0.86, AUROC: 0.99; AUROC for tumors <2 cm: 0.98	AI improves early pancreatic cancer detection, enhancing survival prospects
Alves *et al.* 2022[38]	Deep Learning	242 internal PDAC patients, 361 external patient datasets	nnANet (3 configurations)	nnUNet_MS performed best, achieving an AUC-ROC of 0.91 on external datasets and 0.88 for tumors under 2 cm	Deep learning enhances PDAC detection and diagnostic accuracy

Data Overview:

The datasets in the studies mentioned in Table 6 were used for training, validating, and testing the models. They come from various sources, including publicly available data, private hospital records, Kaggle repositories, and research-specific collections. While some datasets, such as the non-small cell lung cancer (NSCLC) dataset[28,29] and Kaggle repositories,[30] are publicly accessible,[33,36–38] others, including various hospitals[31–33,35–38] and private setting[34] datasets, remain unpublished.

Many datasets are pre-labeled with tumor presence and metadata, while others consist solely of raw CT scans. CT imaging is often integrated with metadata, such as patient demographics and clinical history, to develop survival prediction models. Public datasets were predominantly used for pretraining models, whereas private datasets were used to evaluate model accuracy and applicability across different studies.

Transfer learning studies typically use smaller PDAC-specific datasets for fine-tuning and validation, relying on larger unrelated datasets for pre-training.[28–32] Deep learning studies, on the other hand, require significantly larger datasets for direct training and validation, often sourced from private hospitals or multicenter collaborations.[32,34,35]

Transfer Learning Results:

This section explores the effectiveness of transfer learning-based models for various medical applications, specifically focusing on pancreatic cancer detection and survival prediction. CNN-based transfer learning models have outperformed traditional radiomics-based models commonly used in clinical research. Radiomics-based models are models that use quantitative features extracted from medical images to analyze a disease. As shown in Figure 3, the transfer learning model significantly outperforms radiomics-based models on both IPA and C-index. The IPA tripled when applying CNN-based transfer learning, and the concordance index exceeded 60%.[28] In addition, transfer learning approaches, like the You Only Look Once (YOLO) model, have also shown remarkable precision and sensitivity in identifying pancreatic cancer.[30] In segmentation, transfer learning helps focus on pancreatic cancer regions while excluding unrelated areas, achieving comparable results to methods like CycleGAN.[31] This approach improved key metrics—Dice Similarity Coefficient, Intersection over Union, and Sensitivity—by nearly 2%.[31] Cutting-edge applications, like using a transfer learning model built on Natural Language Processing (NLP) to predict survival based on narrative CT scan reports achieved an AUROC of 0.911 across multiple datasets from different countries, meaning the model demonstrated strong predictive performance in distinguishing between patients who survived and those who did not.[32] These findings highlight the growing impact and potential of transfer learning in advancing medical image analysis and prediction models.

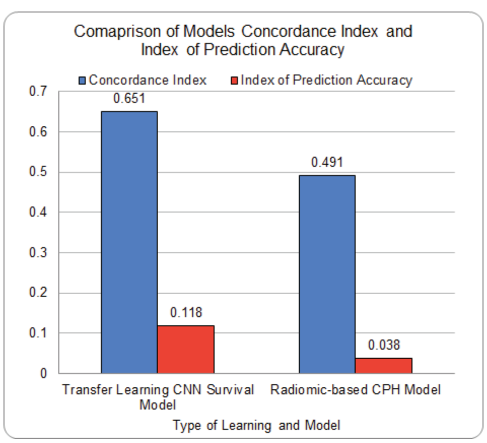

Figure 3: Transfer learning vs radiomic-based model C-Index and IPA comparison. This figure shows the model's respective C-Index and IPA values, demonstrating the superior performance of transfer learning in both IPA and C-index scores.

Transfer learning-based CNN models were the most frequently employed for disease classification, as exemplified by three of the studies.[28-30] CNNs are well-suited for feature extraction and classification, helping cancer detection by comparing abnormalities between images. This has been the standard-based model for transfer learning-based approaches, ranging in studies from 2020 to 2024. However, new architectures have evolved to make cancer detection more accurate and efficient. Some of the newer models include CycleGAN, which can enhance images to make them look more similar to one another. This is useful when you have data from multiple sources. Transfer learning-based models have also leveraged NLP, including ClinicalBert, allowing for the model to learn from medical reports, just like a doctor would. The functional versatility of these models supports the broad applicability of transfer learning in various pancreatic cancer detection tasks.

As seen in Figure 4, while the best transfer learning model achieved an accuracy of 0.88, the deep learning model achieved 0.99. This 0.11 gap is a notable difference in machine learning. The observed accuracy gap likely results from generalization differences where deep learning models are fine-tuned entirely for a target task, whereas transfer learning may be constrained by limited feature adaptation and domain-specific discrepancies between source and target datasets. Though having a worse accuracy, in exploratory and low-stakes settings, including user recommendation or use alongside medical professionals, 0.88 is an acceptable performance in certain cases. This means that transfer learning models in certain real-world applications are suitable for distinguishing between the positive and negative classes to the extent of deep learning. Figures 5 and 6 also show this trend between transfer and deep learning models, where we see transfer learning models obtaining high specificity, sensitivity, and F1 scores matching those of deep learning. The side-by-side comparison reveals similar trends and highlights transfer learning's capacity to adjust to diverse contexts.

Transfer learning has shown substantial promise in medical imaging compared to the current gold standard of doctor analysis. Real-life human doctors must rely on their clinical expertise, patient history, and available imaging to make diagnoses. While highly skilled, the accuracy of human radiologists can be affected by limitations in training, the availability of data, and human error, especially when identifying smaller tumors or in challenging regions like the pancreas. While deep learning models like PANDA offer valuable insights, transfer learning has demonstrated comparable effectiveness, reinforcing its utility in pancreatic cancer detection. In multi-center validation studies, the PANDA model outperformed radiologists in PDAC detection, achieving a 14.7% higher sensitivity and a 6.8% higher specificity.[35] With such results as shown by PANDA, transfer learning has strong potential in PDAC detection that can assist human doctors.

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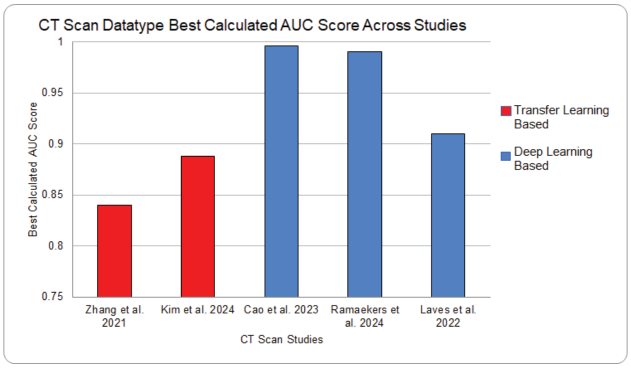

Figure 4: Transfer vs deep learning AUC score comparison. This figure presents the highest AUC scores reported for deep learning, transfer learning, and other AI algorithms in their respective CT scan-based studies. While deep-learning-based approaches outperform transfer learning-based approaches, there remains a promising trend in the performance of off-the-shelf transfer learning models to provide value in new contexts/applications. Note: All used different datasets and models.

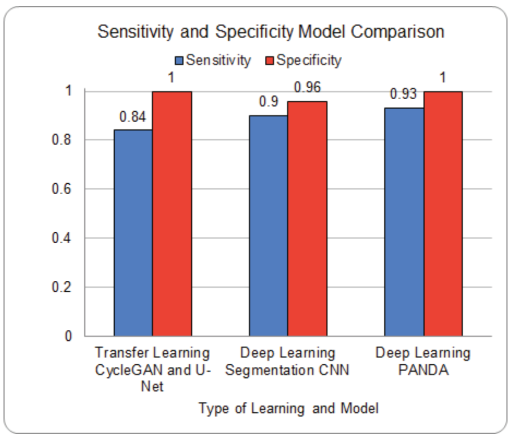

Figure 5: Various model sensitivity and specificity comparison. This figure compares the sensitivity and specificity of various models using both transfer learning and deep learning approaches. Transfer learning models exhibit strong performance in both metrics, rivaling that of deep learning methods.

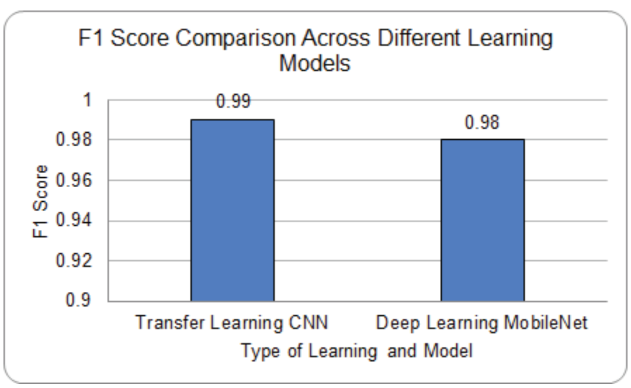

Figure 6: Transfer vs deep learning F1 score comparison. This figure compares the F1 scores of transfer learning and deep learning models. The results show that transfer learning achieves F1 scores comparable to deep learning, demonstrating a strong balance between precision and recall in diagnostic performance.

Ultrasound

Ultrasound Overview:

As a noninvasive imaging technique, ultrasound is typically the first diagnostic step in evaluating suspected PDAC. Ultrasound uses high-frequency sound waves to create real-time pictures or videos of internal organs or other soft tissues, such as blood vessels. A probe transmits sound waves into your body and converts these waves into electrical signals, which are converted into a live image. For PDAC, one would get an abdominal ultrasound to detect the pancreas region. Since ultrasound is a first-level imaging test, most doctors do not consider it definitive evidence for diagnosing PDAC. Due to its limited role as conclusive proof, research on using ultrasound scans as a primary data type for PDAC is scarce, particularly in the context of transfer learning approaches. The other ultrasound technique we decided to use was EUS because it obtains higher-resolution images, which increases the likelihood of tumor detection. Even with its high resolution, as seen in Figure 7, detecting cancerous pancreatic regions remains a huge challenge for doctors and the naked eye. In Figure 7, the blue lines outline the hard areas, the yellow lines outline the soft areas, and the white lines outline the tumor. Doctors measure the stiffness of tissue when detecting cancerous regions.

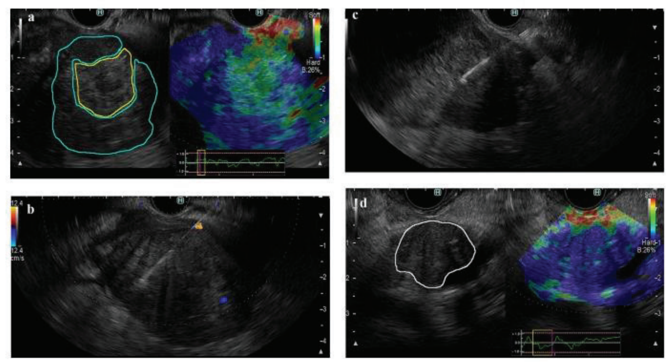

Figure 7: PDAC EUS scan example. An abnormal pancreatic EUS scan that highlights the difficulty of distinguishing cancerous pancreatic regions from non-cancerous ones with the human eye. This image is from Figure 2 of the study: The role of EUS elastography-guided fine needle biopsy in the histological diagnosis of solid pancreatic lesions: a prospective exploratory study.[39]

Ultrasound Studies:

The four studies listed in Table 7 examine ultrasound data and its use in either transfer learning or traditional deep learning approaches. We considered these to be a representative sample, dividing the studies into two based on transfer learning and two based on deep learning.

Table 7: Summary of peer-reviewed studies employing ultrasound data in PDAC research for transfer and deep learning-based approaches.

Study	Type of Learning	Data	Model	Performance	Key Takeaways
Cheng *et al.* 2017[41]	Transfer Learning	5,518 grayscale ultrasound images from 185 studies, labeled into 11 categories	CaffeNet- modified AlexNet; VGGNet- 16-layer CNN; Both pre-trained on ImageNet, retrained FC layers	CaffeNet: 77.3% accuracy, 90.4% top-2 accuracy; VGGNet: 77.9% accuracy, 89.7% top-2 accuracy; both outperformed radiologists (71.7%)	Transfer learning enhances medical imaging analysis, outperforming human experts with limited labeled data.
Baldota *et al.* 2021[40]	Transfer Learning	9,213 ultrasound images converted from endoscopic videos, manually segmented	DenseNet201, pre-trained on ImageNet(pre-trained, fine-tuned for task)	99.88% accuracy, 0.9988 sensitivity, 0.9993 specificity, misclassified only 12 images	DenseNet201 shows promise for real-time computer-aided diagnosis in ultrasound imaging.

Tian *et al.* 2022[43]	Deep Learning	1,213 EUS images from 157 patients (Pancreatic Cancer & Non-Pancreatic Cancer conditions)	YOLOv5m (trained for 300 epochs)	Precision of 0.713, recall of 0.825, mean average precision (mAP@0.5) of 0.831; AUC of 0.85(comparable to the 0.838 AUC achieved by physicians)	YOLOv5m supports real-time pancreatic lesion detection in EUS, aiding clinical decision-making.
Saravi a *et al.* 2024[42]	Deep Learning	126,000 EUS images from 378 exams across four international centers	Trinary CNN: Normal vs. non-mucinous pancreatic cystic neoplasms vs. mucinous pancreatic cystic neoplasms	Accuracy: 99.1% (Normal), 99.0% (MPCN), 99.8% (NMPCN), Differentiation: 94.0% (PDAC vs. PNET)	First global CNN model for pancreatic cystic and solid lesion detection, leveraging diverse datasets to minimize bias.

Data Overview:

The datasets in the studies mentioned in Table 7 were used for training, validating, and testing the models. They come from various sources, including clinical studies,[40] private institutions,[41,42] and hospitals,[43] all of which are unpublished. All the studies required researchers to manually label data.[40–43] The data ranged globally across the studies, with some studies getting their data from multiple hospitals or research centers,[40,42] while others only used data from one source.[41,43] The diversity in data sources helped mitigate demographic bias and improve the robustness of the models in diagnosing pancreatic diseases. Despite variations in dataset sizes and sources, a consistent pre-processing step across studies involved resizing images to 256×256 pixels to standardize input data for transfer learning models.[40,41]

Transfer Learning Results:

The results of transfer learning across these studies highlight its effectiveness in medical imaging in PDAC and other pancreatic disease detection. By leveraging pre-trained convolutional neural networks such as VGGNet, CaffeNet, and DenseNet201, models achieved high classification accuracies, often surpassing human performance.[41,43] For example, VGGNet outperformed radiologists in classifying abdominal ultrasound images,[41] while DenseNet201 achieved near-perfect accuracy (99.9%) in distinguishing pancreatic conditions.[43] Similarly, deep learning models trained on EUS images, such as YOLOv5m and CNN-based classifiers, demonstrated strong performance matching that of transfer learning.[42,43] For example, when tasked with identifying and differentiating pancreatic lesions, deep- learning CNN-based classifiers achieved precision levels exceeding 90% in most cases and effectively distinguished different pancreatic conditions.[42] The ability to fine-tune pre-trained models on relatively small but well-annotated datasets has proven highly effective, reducing the need for large-scale labeled data while maintaining high diagnostic accuracy. Figure 8 demonstrates that transfer learning models consistently outperform human radiologists and perform competitively with, or even surpass, deep learning models in terms of accuracy. This suggests that transfer learning could become a valuable tool in enhancing diagnostic precision in ultrasound imaging, with its performance exceeding humans and deep learning models alike.

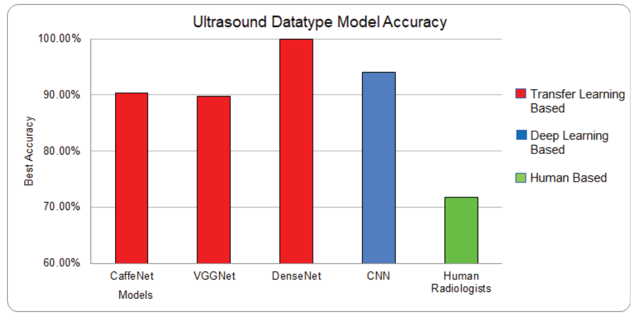

Figure 8: Ultrasound data type model best accuracy. Comparison of accuracy between different ultrasound transfer learning models, both transfer learning and deep learning based, compared to human radiologists. Transfer learning models achieve higher accuracy than radiologists and comparable performance to advanced deep learning models. Note: CaffeNet and VGGNet shared the same data source, but DenseNet and the human radiologists used separate datasets.

Cell Biopsy

Cell Biopsy Overview:

A biopsy is an invasive procedure and remains the current human gold standard for confirming many cancers, including PDAC. Cell biopsies are currently the only way to validate cancer confirmation for a majority of cancers, as doctors remove a piece of tissue or a sample of cells from the body to be tested in a laboratory.[44] Because doctors have to confirm cancers themselves from cell biopsies, the use of the transfer learning approach on cell biopsies isn't as effective and is rather redundant. For this reason, there are limited sources that cover this approach. Figure 9 displays a PDAC cell biopsy example, with arrows indicating the tumor and its growth, black stars marking cancerous regions, and the pink area showing the stroma, illustrating the challenge of visually identifying tumor growth amid surrounding tissue.

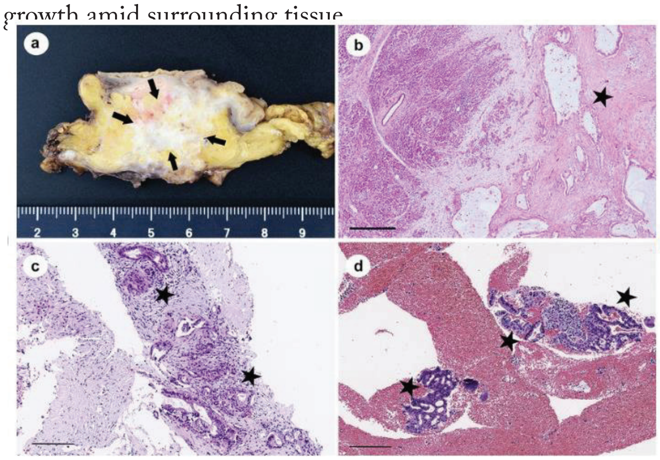

Figure 9: PDAC cell biopsy example. An abnormal pancreatic cell biopsy that illustrates the challenge of visually identifying early tumor growth amid surrounding tissue. This image is from Figure 1 of the study: A deep learning model to detect PDAC on endoscopic ultrasound-guided fine-needle biopsy.[45]

Studies:

The following two studies in Table 8 are focused on cell biopsy data and were categorized based on their methodological approach: transfer learning or deep learning. We selected these studies as representative examples.

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Table 8: Summary of peer-reviewed studies employing cell biopsy data in PDAC research for transfer and deep learning-based approaches.

Study	Type of Learning	Data	Model	Performance	Key Takeaways
Kronberg *et al.* 2022[46]	Transfer Learning	223 PDAC & 161 healthy tissue spots (1 per patient)	ResNet18 CNN	94% accuracy, 90% weighted F1-score	Communicator-driven preprocessing improved label refinement and model accuracy for PDAC detection
Saillard *et al.* 2023[47]	Deep Learning	202 training patients, validated on 598 across four cohorts	PACpAInt	AUC 0.71-0.9	Effective subtype classification, prognostic value, and detection of intratumor heterogeneity, including minor aggressive and transitional tumors

Data Overview:

The datasets in the studies mentioned in Table 8 were used for training, validating, and testing the models. Both used data from hospitals,[42,43] which were private. However, one also used a public dataset[43] in a published repository. Both studies required researchers to manually label the data.[42,43] Kronberg's study used tissue cell data,[42] while Saillard's study used RNA-seq data.[43] Despite variations in dataset sizes and sources, a consistent preprocessing step across studies involved resizing images to 224×224 pixels to standardize input data for their respective models.[42,43]

Transfer Learning Results:

Given the limited number of studies available, no generalizable conclusions can be drawn. Further research is needed on cell biopsy data.

Discussion

Comparisons:

Studies focusing on CT scans, ultrasound, and cell biopsies have demonstrated positive trends in applying transfer learning, yielding results comparable to those of deep learning. Although the number of studies is limited, transfer learning has initially outperformed human accuracy in diagnosis, particularly in detecting tumors smaller than 2 cm. Transfer learning-based CNN models were the most frequently used for disease classification, appearing in six studies. CNNs are well-suited for feature extraction and classification, aiding cancer detection by identifying abnormalities between images. One important consideration when evaluating transfer-learning-based approaches is the data modality used to train the foundational model. As shown across Figures 5 and 8, the aforementioned approaches show enhanced performance in ultrasound contexts relative to CT scans. This may be due to fundamental differences in data and/or data volume used to train and evaluate the models. CT scans are better for capturing static images meanwhile, ultrasound is able to capture real-time movement within organs. Ultrasound studies also used substantially larger datasets for training, validation, and testing compared to CT scans and cell biopsies. However, more studies have been conducted on CT scan data, making it the most prominent field for transfer learning's potential applications. Across all three data types, transfer learning shows a positive outlook, with AUC scores exceeding 0.7 and high accuracy percentages. These findings highlight transfer learning's potential in PDAC detection, including survival modeling, classification, and prediction.

Limitations:

The most significant challenge faced by many studies was the limited availability of data or the absence of a suitable pre-trained model. As stated before, insufficient amounts of data can lead to bias or inaccurate results, limiting the overall reliability of the findings. We believe that making PDAC data, especially CT scans, more publicly available would greatly benefit this field by advancing research and enhancing the development of transfer-learning detection models. Additionally, the lack of relevant pre-trained models poses a challenge, as existing models aren't suited for transfer learning on PDAC. Most existing pre-trained models in medical imaging are trained on general radiology datasets (e.g., chest X-rays, brain MRIs) rather than CT scans, which have unique features that aren't captured but are necessary for cancer detection in such a hidden organ. This results in models extracting information that isn't relevant to PDAC detection, compromising performance and usefulness. Lastly, as the AI field continues to advance, a lack of public trust can hinder the adoption of transfer learning-based PDAC detection results even when surpassing human performance. To address this, it's crucial to provide clearer validation studies while fostering collaboration and transparency between researchers, clinicians, and patients.

Future Directions:

As transfer learning PDAC detection continues to evolve, future research should focus on refining current methodologies and addressing existing limitations to enhance clinical applicability. To address the lack of data, we suggest that researchers generate high-quality synthetic data, which helps mitigate the lack of real-world PDAC datasets, including creating realistic CT scans to train models. Synthetic data still creates realistic data, but doesn't require private institutions to give personal data away. Another way to enhance transfer learning approaches is to combine them with other forms of learning, like few-shot learning. Few-shot learning enhances model performance by utilizing prior knowledge from related tasks, despite requiring only a minimal number of labeled examples. Combining few-shot learning with transfer learning could help AI models generalize better for PDAC detection, especially when past studies have shown that data is extremely scarce. As for models, utilizing pre-trained models from cancers with similar imaging characteristics (e.g., liver, pancreatic, or gastrointestinal cancers) can enhance PDAC detection when domain-specific datasets are scarce. This approach can help extract more relevant features and improve generalization. For transfer learning to truly advance, practical implementation is key.

All of the studies reviewed in this analysis are experimental in nature, meaning they were conducted in controlled research settings and primarily involve preclinical or early-stage investigative methodologies. To date, none of these studies have undergone validation through large-scale, peer-reviewed clinical trials, and thus their findings should be interpreted with caution until further clinical evidence is established. However, from the initial positive outlook on the use of transfer learning-based approaches for PDAC detection, we suggest that researchers start bridging the gap between research and real-world clinical applications. Achieving clinical integration will require rigorous validation, alignment with regulatory standards, and performance evaluation using real-world patient data. These transfer learning-based models must be interpretable, user-friendly, and aligned with clinical guidelines to gain trust and adoption among healthcare professionals. One way to go about this is to compare doctor analysis with transfer learning model analysis and assess their performance to determine which areas the model or human excels in. Additionally, this comparative analysis can help identify specific strengths and weaknesses of the model, guiding further improvements. By continuously refining these models through real-world feedback and aligning them with established clinical workflows, transfer learning-based PDAC detection can become a valuable tool that will improve diagnostic accuracy and patient outcomes. This approach may facilitate broader data availability and further advancement in transfer learning-based PDAC detection models.

Conclusion

Transfer learning has demonstrated significant promise in the detection and analysis of PDAC. By leveraging pre-trained models, transfer learning has been proven to enhance diagnostic accuracy, reduce data requirements, and improve computational efficiency compared to traditional deep learning approaches. Our review highlights its effectiveness across multiple imaging modalities, including CT scans, ultrasound, and cell biopsies, with CT scans being the most widely studied and most promising application. Despite these advancements, there still exist many limitations, including the lack of high-quality datasets and the need for more specialized pre-trained models for PDAC detection. Future research should prioritize improving model interpretability, promoting data transparency, and fostering public trust to advance the application of AI technologies in improving PDAC detection and patient outcomes.

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Code and Data Release

This work is a comprehensive literature review and does not involve new experimental data or code. All reviewed studies were identified through searches on Google Scholar. All data are available from the cited publications.

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