Transfer Learning for Pancreatic Ductal Adenocarcinoma: A Comprehensive Review

Jonathan Song

Abstract

Transfer learning stands as a breakthrough methodology within artificial intelligence, offering unprecedented advantages in medical imaging and cancer diagnosis. Transfer learning needs less data than deep learning to build models for new problems. This paper explores how transfer learning techniques can improve both the detection and diagnostic accuracy of Pancreatic Ductal Adenocarcinoma (PDAC), a cancer known for its high mortality rate and difficulty in early diagnosis. 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's efficacy 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.

Introduction

Known as a "silent" disease due to the lack of symptoms in early stages, pancreatic cancer is one of the hardest diseases to detect. Due to its location in the pancreas, surrounded and hidden behind other organs, pancreatic tumors are nearly impossible to detect during a routine medical checkup. Pancreatic cancer often goes undetected due to a lack of symptoms in its early stages. This allows the disease to progress unchecked until it reaches more advanced stages. 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] Even though pancreatic cancer makes up 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. 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 accounts for 90% of all cases of pancreatic cancer.[1]

There are several methods that clinicians currently use to detect PDAC, including Computerized 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.

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, possibly eliminate the need for surgery, and monitor internal parts of your body	Expensive and consumes lots of energy, exposure to low amounts of radiation, contrast CT scans have exposure to contrast dye, semi-invasive
PET Scan[2,4]	A small dose of radioactive sugar is injected and collected by cancer cells, which is shown on images and is often used alongside CT scans		
MRI[3,5]	Uses magnetic fields to provide a clear and detailed picture of an organ	Superior imaging depictions for soft tissues, no radiation, noninvasive	Strong magnetic forces, which can have safety concerns, are expensive
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	High diagnostic accuracy, tissue sampling ability	Operator dependency, potential internal complications, expensive, not available in some countries, minimally-invasive
Ultrasound *[7]	A transducer is pressed against the area that is being studied, which sends and	Inexpensive, non-invasive, quick, good for	Can't penetrate bone, air, or deep structures

	collects sound waves to map an image	soft tissue imaging	
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 diagnosing, tumor staging, and monitoring treatments	Invasive, potentially internal compilation, expensive, operator dependency

Despite the existence of these methods shown in Table 1, the ability to detect PDAC is still a work in progress. In recent years, advancements in 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, 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.

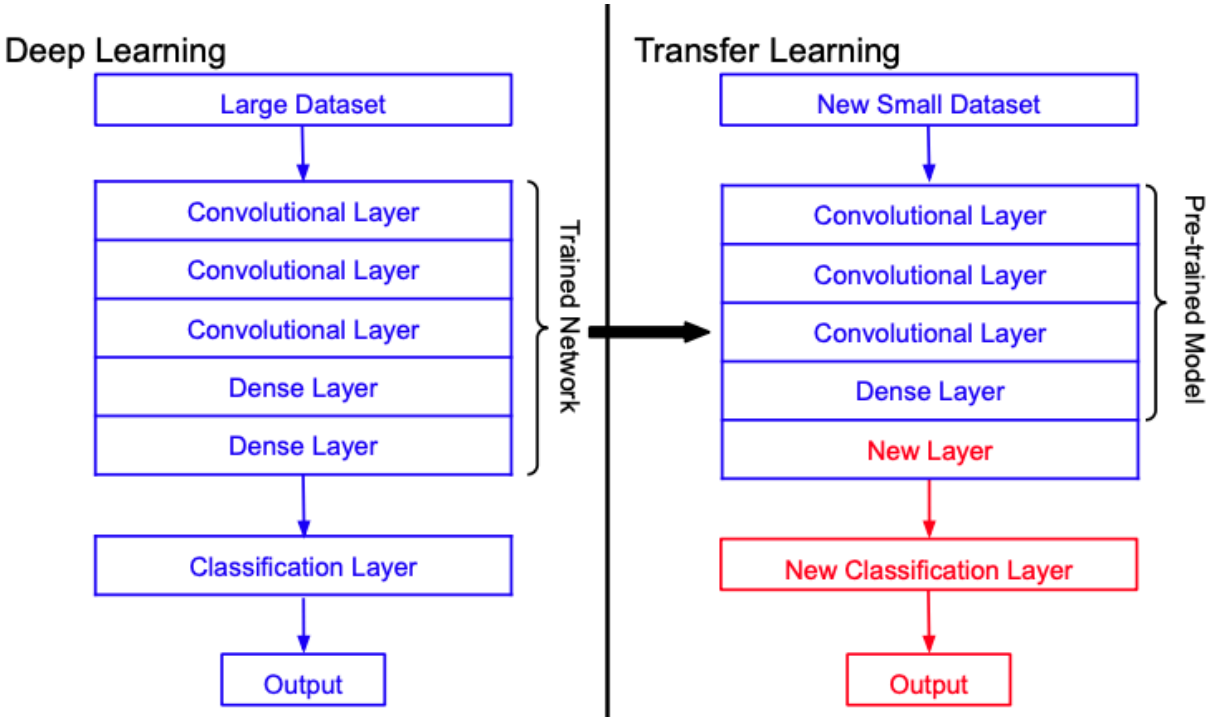

Figure 1. *Deep Learning vs Transfer learning architecture.* The left half represents a deep learning architecture, and the right half represents a transfer learning architecture. The blue portion indicates nodes of a deep learning model, and the red portion is the re-trained elements (last layer of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

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] Deep learning was first used with cancer data in the early 2000s for cancer classification and subtype detection. This involves utilizing deep learning to analyze 3D images from Digital Breast Tomosynthesis for breast cancer detection. 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 and discovery by analyzing genomic and epigenomic data to advanced early cancer detection, deep learning combines data from all sorts of medical fields to get 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. Many of the studies included in this review are based on deep learning.

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. Transfer learning requires fewer data than traditional deep learning models, making it more efficient for developing solutions to novel problems. Figure 1 shows a comparison between the architectures of deep learning and transfer learning.

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] Nowadays, transfer learning can be applied to almost all forms of image classification, from ultrasound images to CT scans. 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.*

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
Classificatio[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 tumour 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.

Table 3. *List of metrics and what they measure,*

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 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

Data Collection

We reviewed 28 research articles and selected 17 to use, all of which belonged to three major data types: CT Scan, ultrasound, and cell biopsies. We found all our sources on Google Scholar with the keywords we used below in Tables 4 and 5.

In examining the three methods, we observed a significantly greater volume of studies on deep learning compared to transfer learning. Additionally, prior research utilizing transfer learning for the analysis of PDAC CT scans was more readily available than for ultrasound imaging. 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 and can yield less accurate results, making them the most prominent application of transfer learning to achieve better outcomes. Cell biopsy as the data source was heavily researched too, but a majority of the articles don't relate to using cell biopsies for transfer or deep learning, likely because cell biopsy is the gold standard method that many doctors use to confirm if a patient has PDAC or not. Despite its promising performance, transfer learning has been applied to ultrasound data less frequently than to other imaging modalities.

Table 4. Data type frequency on Google Scholar without applying any time restriction.

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

Table 5. *Data type frequency on Google Scholar from 2022 to 2025.*

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 was the total generated results, however, we focused our research on recent progress, so we further classified results within the past five years, 2022 to 2025. Table 5 was generated using the same methodology as Table 4; however, it reflects the number of entries on Google Scholar from 2020 to the present, rather than all-time results as in 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. Transfer learning is still a developing concept that isn't fully recognized as its keyword yet by Google Scholar, so it ends up giving a far wider range of research rather than those solely focused on transfer learning. On Google Scholar, when searching for sources, we encountered far more deep learning papers analyzing all three data types regarding PDAC compared to transfer learning.

CT Scan

3.1 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 is 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' location behind other organs, it needs contrast for doctors to study it. Non-contrast CT scans, on the other hand, use no agent. The CT scan is 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 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. PDAC, as visualized below in Figure 2, illustrates the challenge of distinguishing it from healthy tissue due to its subtle visual differences and complex tumor microenvironment.

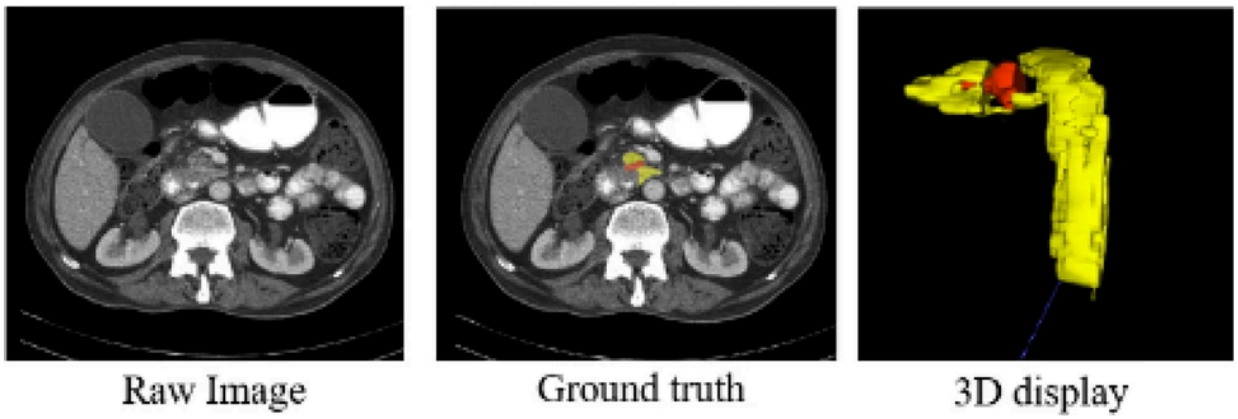

Figure 2. *PDAC CT Scan Example*
An abnormal pancreatic CT scan with a red region denoting PDAC and yellow regions denoting normal pancreas tissue. This image highlights the difficulty of distinguishing cancerous pancreatic regions from non-cancerous ones with the human eye. This image is from Figure 1 of the study: Segmentation of PDAC and surrounding vessels in CT images using deep convolutional neural networks and texture descriptors.[47]

3.2 Studies

The following 11 studies focused on CT scan data type and whether it was transfer or deep learning. These are a representative sample, splitting the studies into 5 transfer learning-based and 6 deep learning-based studies. The transfer learning studies leverage pre-trained models to enhance diagnostic accuracy and predictive performance, particularly in cases with limited data availability. These approaches demonstrate the effectiveness of transfer learning in refining prognostic assessments, segmentation of medical images, and improving early cancer detection. Conversely, deep learning studies implement custom-built neural networks trained

from scratch to identify patterns within extensive datasets. Both deep learning and transfer learning models have been employed to analyze PDAC CT scans, demonstrating varying performance levels while showcasing significant potential for future applications, such as early prediction of PDAC.

Table 6. *Studies focused on the data type of CT scans.*

Study	Type of Learning	Data	Model	Performance	Key Takeaways
Zhang et al. 2020[27]	Transfer Learning	3 cohorts: 422 NSCLC patients, 68 PDAC patients, 30 independent PDAC patients	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[28]	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[29]	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[30]	Transfer Learning	104 PDAC patients, dual-phase imaging from Changhai Hospital of	CycleGAN, U-Net	Dice: 81.57%, IoU: 71.35%, Sensitivity: 84.32%, Specificity: 99.86%	High segmentation accuracy, surpassing benchmarks in pancreatic imaging

		Naval Military Medical University			
Kim et al. 2024[31]	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[32]	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[33]	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[34]	Deep learning	3208 patients (training), 6239 (validation across 10 centers),	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

		20,530 real-world cases			
Gandikota et al. 2023[35]	Deep Learning	500 samples (two classes)	W-Net + GhostNet + Deep Echo State Network	Accuracy: 96.98–99.02%, Precision: 97.18–99%	TSADL-PCSC approach outperforms existing methods
Ramaekers et al. 2024[36]	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[37]	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

3.3 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[27,28] and Kaggle repositories,[29] are publicly accessible,[32,35–37] others, including various hospitals[30–32,34–37] and private setting[33] 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.[27–31] Deep learning studies, on the

other hand, require significantly larger datasets for direct training and validation, often sourced from private hospitals or multicenter collaborations.[31,33,34]

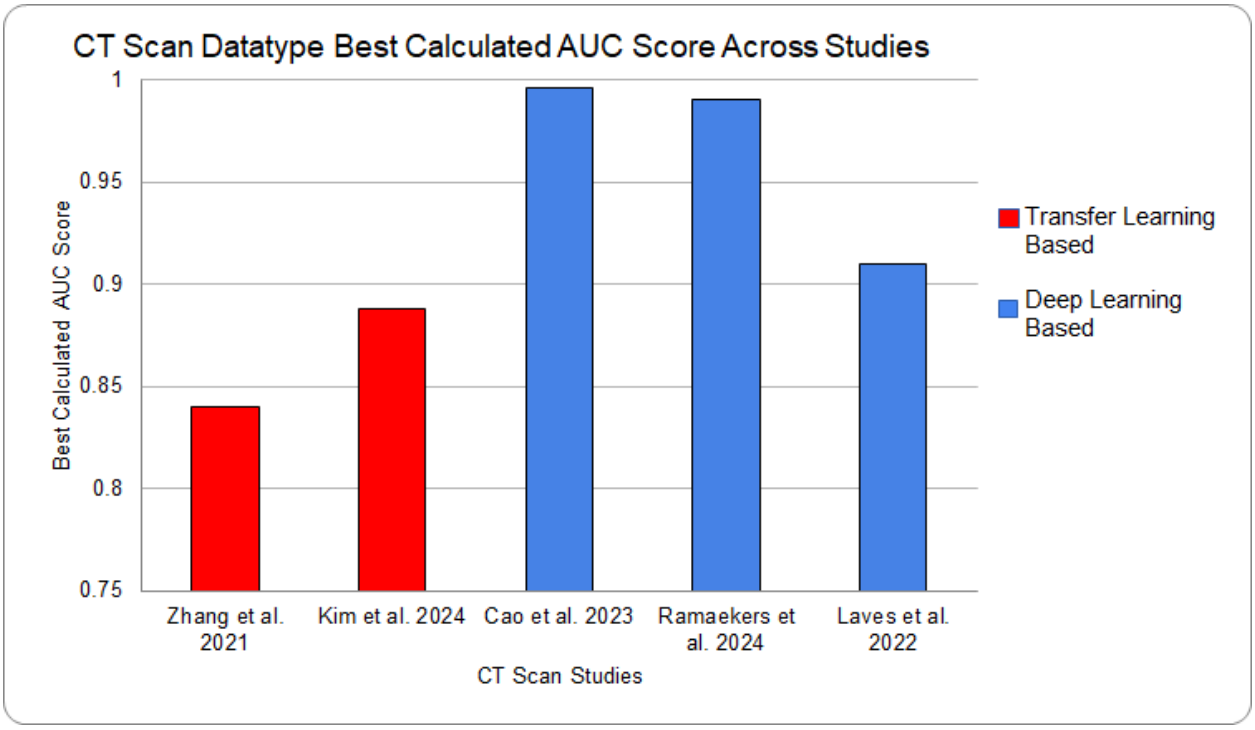

Figure 3. *CT Scan Datatype Best Calculated AUC Score*
Shows the Best AUC score of Deep Learning, Transfer Learning, and AI algorithms in their respective study based on CT scans.
Note: All used different datasets and models

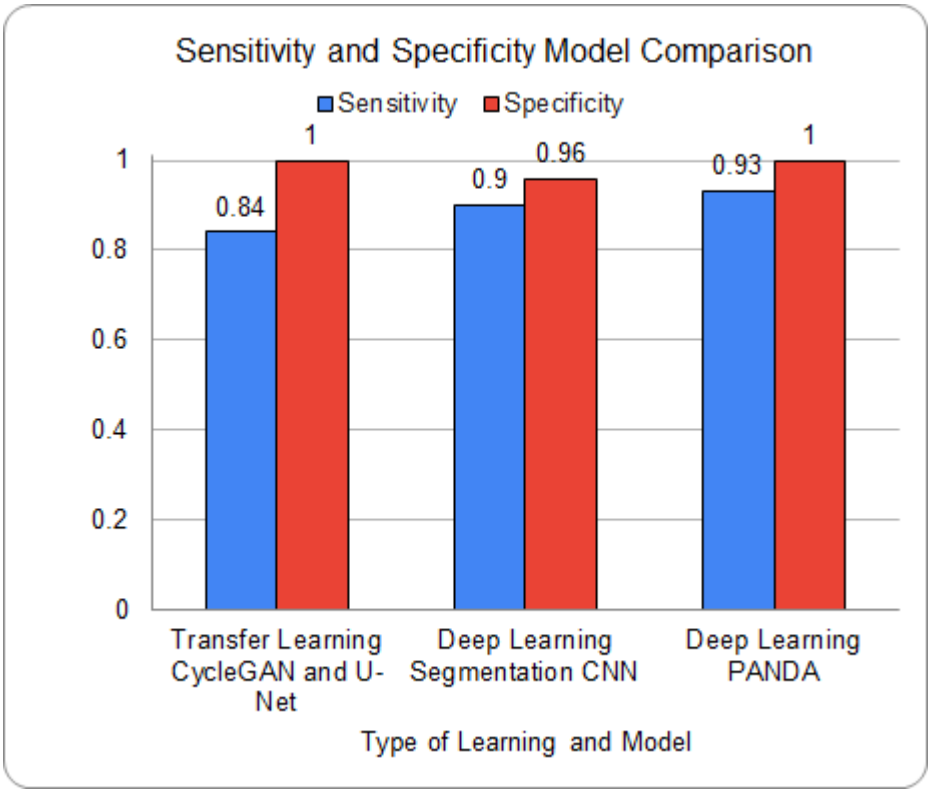

Figure 4. Shows Sensitivity and Specificity Comparison among different models of both transfer and deep learning.

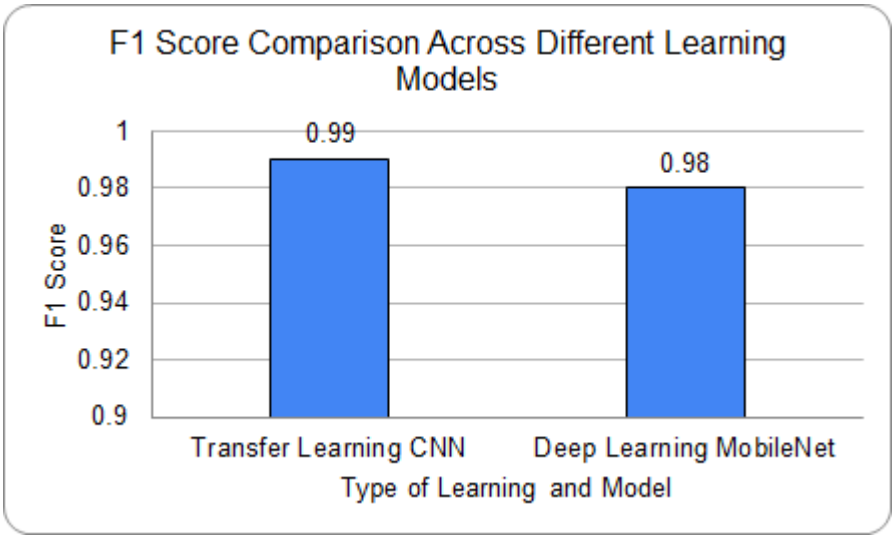

Figure 5. Shows F1 Score comparison between a transfer and a deep learning model

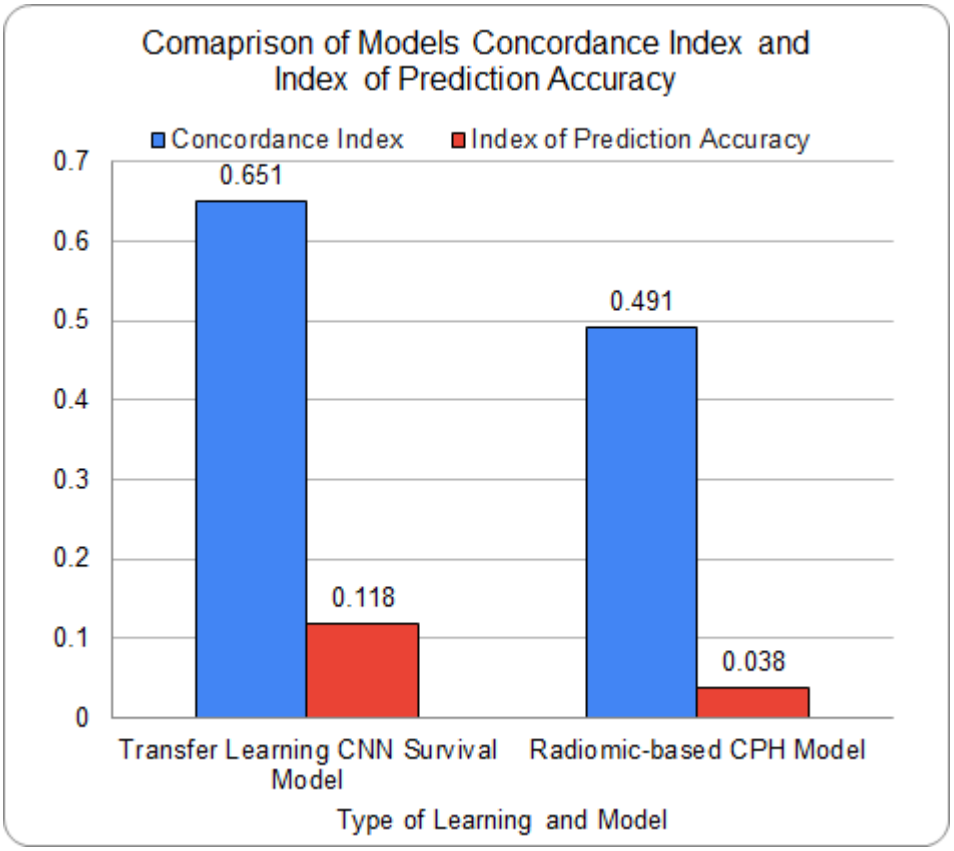

Figure 6. Shows model's respective C-Index and IPA between transfer learning and radiomics-based models

3.4 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. Convoluted Neural Network-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. Figure 6 shows transfer learning models outperforming radiomic based models. The IPA tripled when applying CNN-based transfer learning, and the concordance index exceeded 60%.[27] In addition, transfer learning approaches, like the You Only Look Once (YOLO) model, have also shown remarkable precision and sensitivity in identifying pancreatic cancer.[29] In segmentation, transfer learning helps focus on pancreatic cancer regions while excluding unrelated areas, achieving comparable results to methods like CycleGAN.[30] This approach improved key metrics—Dice Similarity Coefficient, Intersection over Union, and Sensitivity—by nearly 2%.[30] Cutting-edge applications like using a transfer learning model built on 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.[31] These findings highlight

the growing impact and potential of transfer learning in advancing medical image analysis and prediction models.

Transfer learning-based CNN models were the most commonly used for disease classification in four of the studies. CNNs are well suited for feature extraction and classification, helping cancer detection through 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.

Transfer Learning models have shown promising performance compared to that of Deep Learning as seen in Figure 3 with AUC scores of all models consistently above 0.8. Figure 4 and Figure 5 also show this trend between transfer and deep learning models where we see transfer learning models obtaining high specificity, sensitivity, and F1 scores matching that of deep learning.

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.[34] With such results as shown by PANDA, transfer learning has strong potential in PDAC detection that can assist human doctors.

Ultrasound

4.1 Ultrasound Overview

Ultrasound is a noninvasive imaging test usually used as a first scan or test when looking at 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.

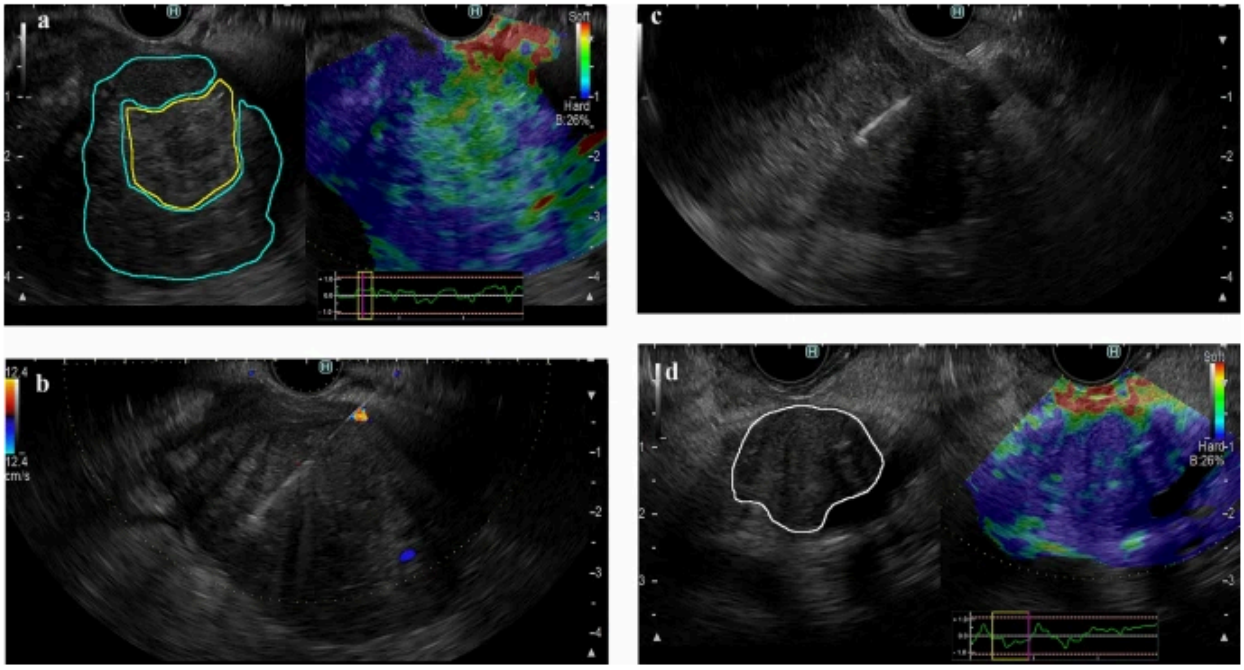

Figure 7. PDAC EUS *Scan Example*
An abnormal pancreatic EUS scan with the blue line outlining hard areas, the yellow line outlining soft areas, and the white line outlining the tumor. Doctors measure the stiffness of tissue when detecting cancerous regions. This image highlights the difficulty of distinguishing 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.[45]

4.2 Ultrasound Studies

The following four studies focused on the ultrasound data type and whether it was transfer or deep learning. 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. Studies focused on the datatype of ultrasound, using deep learning or transfer learning

Study	Type of Learning	Data	Model	Performance	Key Takeaways
Cheng et al. 2017[38]	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[39]	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[40]	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.
Saravia et al. 2024[41]	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	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.

			neoplasms		

4.3 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,[39] private institutions,[38,41] and hospitals[40] all of which are unpublished. All the studies required researchers to manually label data.[38–41] The data ranged globally across the studies, with some studies getting their data from multiple hospitals or research centers,[39,41] while others only used data from one source.[38,40] 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 preprocessing step across studies involved resizing images to 256×256 pixels to standardize input data for transfer learning models.[38,39]

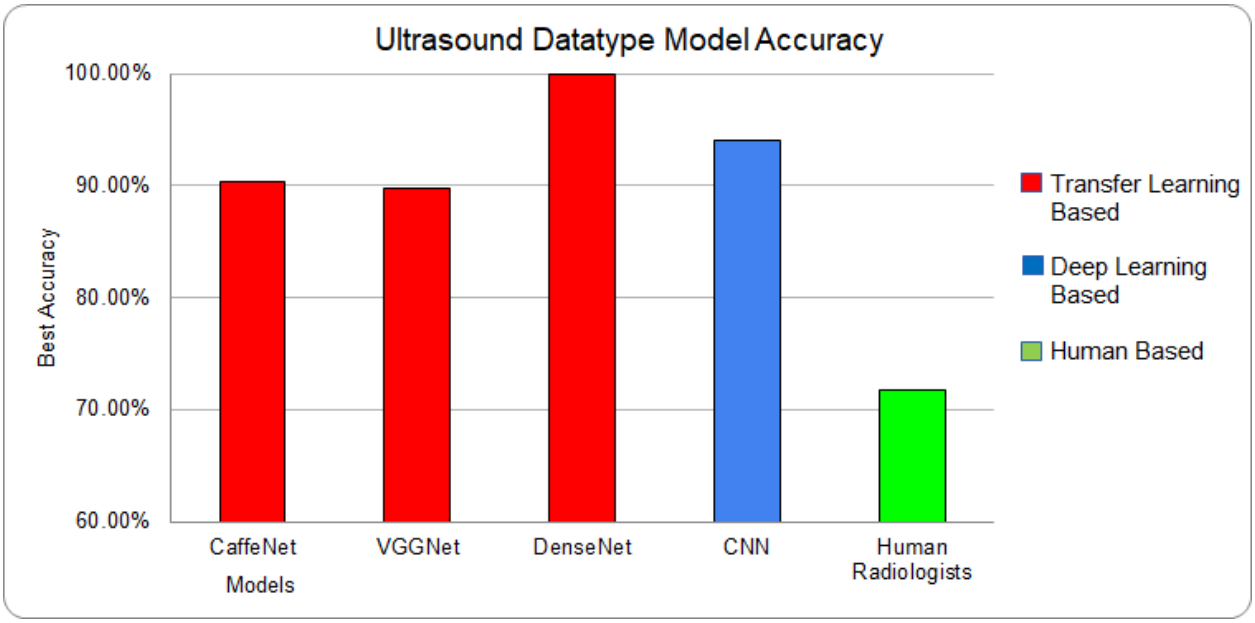

Figure 8. *Ultrasound Data Type Model Best Accuracy*
Comparison of accuracy between different ultrasound transfer learning models, both transfer learning and deep learning based, compared to human radiologists. Note: DenseNet used different data than CaffeNet, VGGNet, and the Human Radiologists

4.4 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.[38,40] For example, VGGNet

outperformed radiologists in classifying abdominal ultrasound images,[38] while DenseNet201 achieved near-perfect accuracy (99.9%) in distinguishing pancreatic conditions.[40] Similarly, deep learning models trained on EUS images, such as YOLOv5m and CNN-based classifiers, demonstrated strong performance matching that of transfer learning.[40,41] For example, when tasked with identifying and differentiating pancreatic lesions, CNN-based classifiers achieved precision levels exceeding 90% in most cases and effectively distinguished different pancreatic conditions.[41] 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.

Cell Biopsy

5.1 Cell Biopsy Overview

A biopsy is an invasive procedure and the current human gold standard to confirm many types of 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 below is an example of a cell biopsy for PDAC.

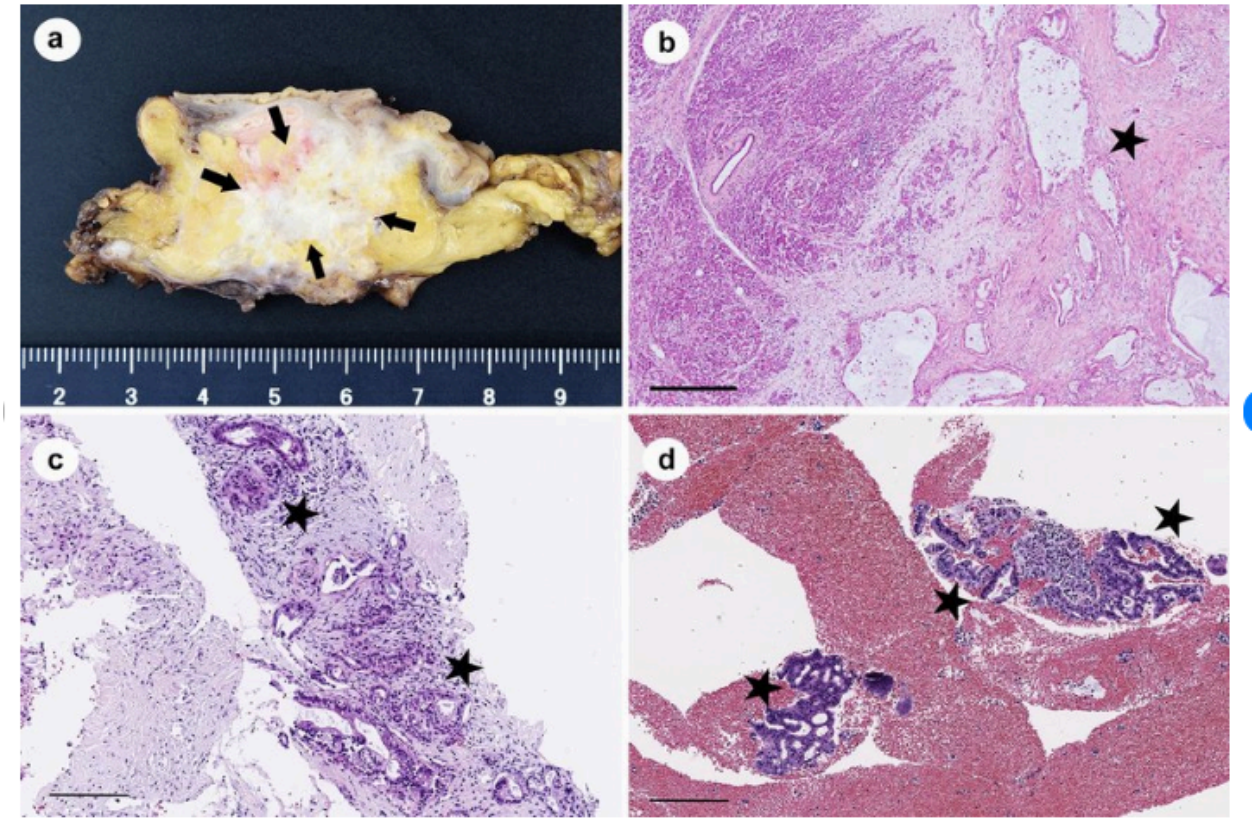

Figure 9. *PDAC Cell Biopsy Example*
An abnormal pancreatic cell biopsy with the arrows pointing toward the tumor and its growth, the black stars indicate cancerous cell regions, and the pink area is the stroma. This image highlights the difficulty of distinguishing cancerous pancreatic regions from non-cancerous ones with the human eye. This image is from Figure 1 of the study: A deep learning model to detect pancreatic ductal adenocarcinoma on endoscopic ultrasound-guided fine-needle biopsy.[46]

5.2 Studies

The following two studies 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.

Table 8. Studies focused on the Datatype of Cell Biopsies.

Study	Type of Learning	Data	Model	Performance	Key Takeaways
Kronberg et al. 2022[42]	Transfer Learning	223 PDAC & 161 healthy tissue spots (1 per	ResNet18 CNN	94% accuracy, 90% weighted	Communicator-driven preprocessing improved label refinement and model accuracy for PDAC

		patient)		F1-score	detection
Saillard et al. 2023[43]	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

5.3 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 RNAseq 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]

5.4 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

6.1 Comparisons

Transfer learning-based CNN models were the most commonly used for disease classification being used in 6 studies. CNNs are well-suited for feature extraction and classification, facilitating cancer detection by comparing abnormalities between images. This has been the standard based model for transfer-learning based approaches 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 look more similar to one another, which is useful when one has data from multiple sources. Transfer learning-based models have also leveraged NLP, including ClinicalBert, allowing for the model to learn from medical reports, similar to how a doctor would. These models have varying functions suited for different tasks, allowing transfer learning to be applicable in a wide range of pancreatic cancer detection applications.

CT Scan, Ultrasound, and Cell biopsy-focused studies have shown positive trends of using transfer learning, showing results that are on-par with that of deep learning. With the limited

studies, transfer learning initially has shown better diagnosis results than human performance, including accuracy, especially when detecting tumors smaller than 2 cm. The amounts of data that Ultrasound studies used for training, validating, and testing the models were far greater than that of CT scans and cell biopsies. However, there were more studies done on the CT scan data type compared to the other two, making it the most prominent field in which transfer learning has potential. All three data types show that transfer learning has a positive outlook, with AUC scores all above 0.7 and high percentage accuracy. They also show how transfer learning has many potential uses in detecting PDAC, including survival models, classification, and predictions.

6.2 Limitations

The largest issue many of the studies encountered was either the lack of data or a relevant 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 if they perform better compared to humans. To address this, it's crucial to provide clearer validation studies while fostering collaboration and transparency between researchers, clinicians, and patients.

6.3 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 see how their performance compares and in which areas the model or human does better. 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 Pancreatic Ductal Adenocarcinoma (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. Moving forward, it is essential that researchers enhance model interpretability, publicize data, and increase public trust to open a new doorway of using AI technology to better detect PDAC and save lives.

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