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SURVEY

Automatic Segmentation of Pancreas and Pancreatic Tumor: A Review of a Decade of Research

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ABSTRACT In the current era of machine learning and radiomics, one of the challenges is the automatic segmentation of organs and tumors. Tumor detection is mostly based on a radiologist's manual reading, which necessitates a high level of professional abilities and clinical experience. Moreover, increasing the high volume of images makes radiologists' assessments more challenging. Artificial intelligence (AI) can assist clinicians in diagnosing cancer at an early stage by providing a solution for assisted medical image analysis. The automated segmentation of tumor is better realized through conventional segmentation methods and, nowadays, through machine learning and deep learning techniques. The segmentation of abdominal organs and tumors from various imaging modalities has gained much attention in recent years. Among these, pancreas and pancreatic tumor are the most challenging to segment and have recently drawn a lot of attraction. The main objective of this paper is to give a summary of different automated approaches for the segmentation of pancreas and pancreatic tumors and to perform a comparative analysis using various indices such as dice similarity coefficient (DSC), sensitivity (SI), specificity (SP), precision (Pr), recall and Jaccard index (JI), etc. Finally, the limitations and future research perspectives of pancreas and tumor segmentation are summarized.

INDEX TERMS Deep learning, machine learning, pancreas segmentation, pancreatic ductal adenocarcinoma, tumor.

I. INTRODUCTION

In clinical practice, radiologists help in the visual analysis of various anatomical structures. Small changes in form, size, or structure can indicate illness and aid in the confirmation of a diagnosis. Manual readings with radiographic images, such as computer tomography scan (CT) or magnetic resonance imaging (MRI), are tedious and can lead to inter and intra-operator variability. Moreover, for quantitative radiographic image analysis with machine learning which has shown widespread application in clinical decision making, segmentation of organs or tumor plays an important role.

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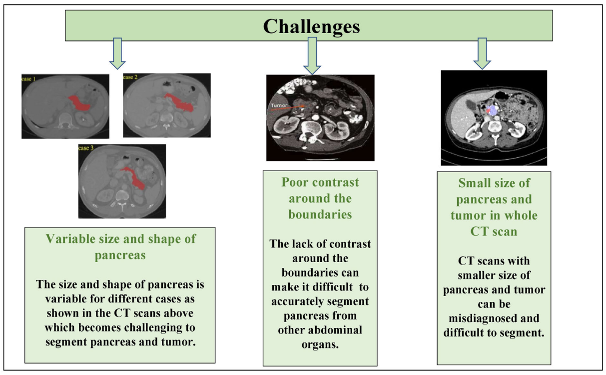

FIGURE 1. Major challenges in segmentation of pancreas and pancreatic tumor.

Automatic systems with artificial intelligence can assist radiological experts in detecting and diagnosing disease and thus improve treatment management. One such disease that requires automated segmentation is pancreatic cancer. One of the most serious illnesses, pancreatic cancer, is becoming more common. According to the global cancer observatory (GLOBOCAN) 2020 statistics, pancreatic cancer accounted for approximately 466,003 deaths worldwide, with 54,277 fatalities reported in the United States in the same year [1].

The most prevalent kind of pancreatic cancer, pancreatic ductal adenocarcinoma (PDAC), arises from the exocrine glands and ducts of the pancreas [2]. Despite improvement in treatment techniques for cancer care, five year survival rate for PDAC is only 10% [3] due to its late diagnosis and lack of effective treatment. More than half of the patients are with metastasis, and 30% with locally advanced disease at the time of diagnosis. As the mortality and incidence rate of pancreatic cancer is continually rising globally, there is an unmet need to enhance the survival outcomes of individuals affected by this disease through the implementation of advanced diagnostic and therapeutic interventions. Recent studies show that patients diagnosed at stage-I can have the most favorable outcome, with a 5-year survival rate reaching up to 80% [4]. Thus, better detection of early-stage disease is a tremendous opportunity to improve PDAC prognosis.

However, detection and segmentation of PDAC is often challenging and vary due to irregular contours and ill-defined margins [5], as shown in FIGURE 1. In addition, in the past decade, with the advancement of imaging technology, radiographic images are being widely investigated with machine learning to develop imaging biomarkers of diagnosis, progression, outcome, and response prediction [6]. However, these techniques highly depend on manual segmentation. As compared to the liver, spleen, and other abdominal organs, the segmentation of the pancreas is challenging as pancreas shape, size, and position are different between individuals [7], [8], [9].

Automated segmentation of pancreas and pancreatic tumor techniques thus can help radiologists not only in proper detection and diagnosis but also in developing more generalized imaging biomarkers for pancreatic cancer. Several approaches have been proposed for automated segmentation of pancreas and pancreatic tumor using different techniques. However, the methods with unsupervised learning, such as clustering, region growing, threshold based methods, etc., did not provide satisfactory performance.

Deep learning-based segmentation techniques have recently seen widespread implementation and have outperformed traditional segmentation techniques in terms of performance. These models consist of hierarchical architecture with different layers. Deep learning with convolutional neural networks (CNN) is the most successful architecture for image analysis. Neural networks, consisting of neurons with parameters and activation functions, have been utilized to extract and combine image features, enabling the development of diagnostic models.

The neural network is composed of neurons with parameters and activation functions to extricate and merge the image features, enabling the development of diagnostic models. In diagnosis and segmentation of various diseases such as diabetic retinopathy [10], liver masses [11], and skin cancer [12] CNN has achieved a better accuracy than conventional methods. Discovering the practicality of CNN in pancreatic cancer segmentation has major implications discussed in pertinent sections. This paper aims to comprehensively review the studies based on the segmentation of the pancreas and pancreatic tumor by using various conventional, unsupervised and supervised approaches, including deep learning methods. The paper also discusses the current challenges in pancreatic tumor segmentation and the future scope of such techniques.

FIGURE 2 represents the detailed outline of the literature review paper.

The subsequent sections of the paper are as follows. Section II focuses on the database selection method. Section III describes the statistical analysis of AI in pancreatic cancer segmentation. Section IV addresses various imaging modalities. Section V presents a detailed review of various pancreas and pancreatic tumor segmentation techniques. Section VI describes the evaluation metrics used in segmentation. Section VII provides an overview of the experimental datasets. Section VIII discusses the findings and insights derived from the review. Section IX summarizes the overall review. Finally, Section X concludes the paper by outlining the future approaches for pancreas and tumor segmentation.

II. DATABASE SELECTION METHOD

A comprehensive search for pancreas and pancreatic tumor segmentation was performed to identify relevant scholarly articles for this survey. The search included prestigious scientific papers from reputed publishers in digital libraries like ScienceDirect, Springer, IEEE Xplore, PubMed, etc. Additionally, annual challenges like the Medical Segmentation Decathlon (MSD) were reviewed. In addition, the

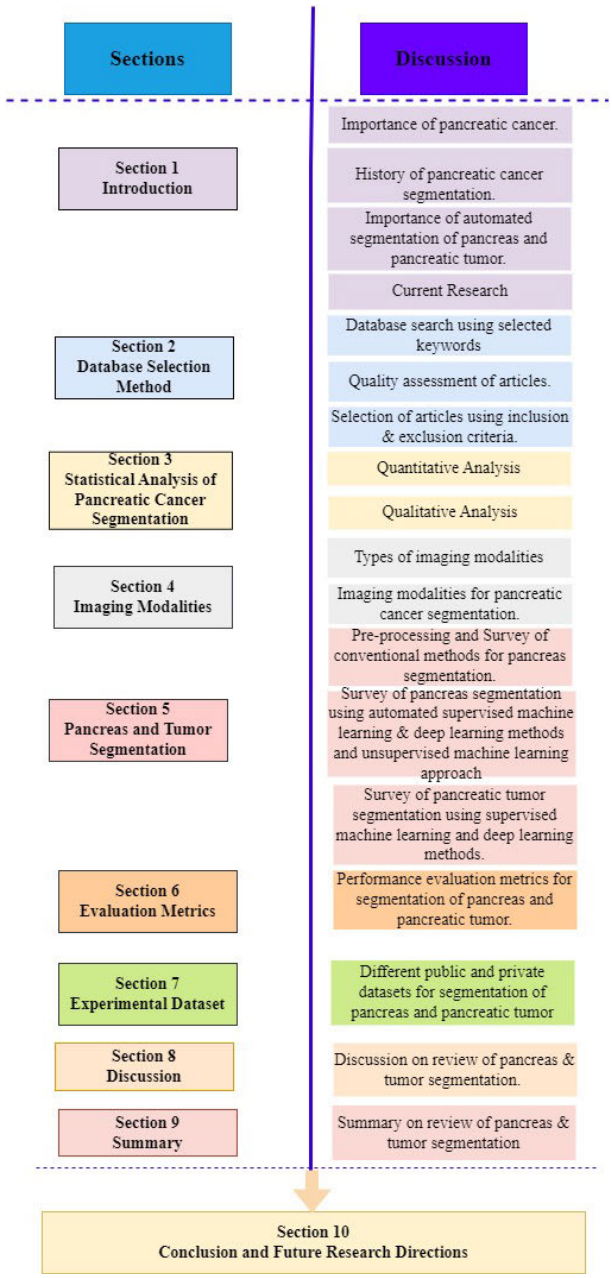

FIGURE 2. Outline of Literature Review.

search extended to include databases such as Google Patents, and the Web of Science, where search keys such as "pancreas", "pancreatic cancer", "segmentation", "artificial intelligence", "machine learning", and "deep learning" were used.

The title and abstract of the articles were assessed as a part of the screening process, and then the full text review was performed for the selected articles. The collected data included information about the authors, article/report title, year, imaging modality, segmentation method, dataset, and algorithm performance. The goal of this survey is to offer a comprehensive analysis of techniques employed for pancreas

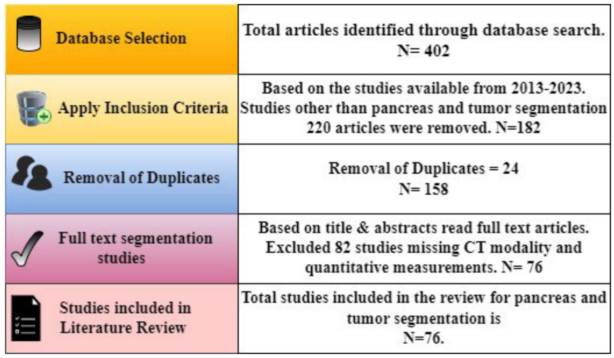

FIGURE 3. Implementation of literature review.

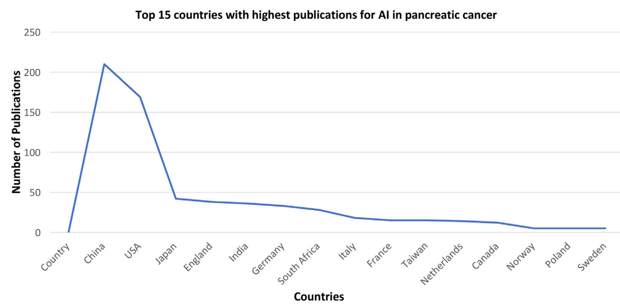

FIGURE 4. Analysis of top 15 countries with publication records.

and pancreatic tumor segmentation. FIGURE 3 represents flow of literature review conducted.

III. STATISTICAL ANALYSIS OF PANCREATIC CANCER SEGMENTATION

Web of Science database is used for the analysis of pancreatic cancer segmentation. Web of Science is one of the most common and acknowledged databases in bibliometric analysis. The search terms used were "pancreatic" OR "pancreas" OR "image segmentation" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "convolutional neural network". The publication date range was restricted to 2013 to 2023. The documents were restricted to articles and reviews. VOSviewer and Microsoft Excel are used for the representation of analysis.

A. QUANTITATIVE ANALYSIS

The quantitative analysis provides an overview of various countries having research in artificial intelligence for pancreatic cancer and an analysis of total publications and citation records for pancreatic cancer segmentation across the globe.

Major countries around the world have received attention for research in pancreatic cancer segmentation using AI. Among those, 15 countries with the highest publication record for pancreatic cancer were observed and shown in FIGURE 4. According to the figure, China is the country with the highest number of publication records for pancreatic cancer, followed by the United States.

The analysis of the total number of publications worldwide and the total number of citations from 2013 to 2023 is depicted in FIGURE 5. The graph clearly illustrates a

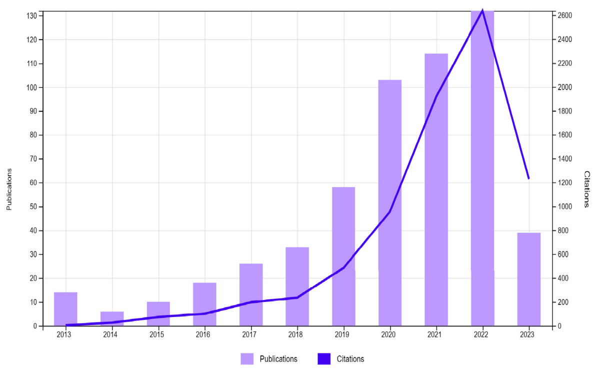

FIGURE 5. Number of publications.

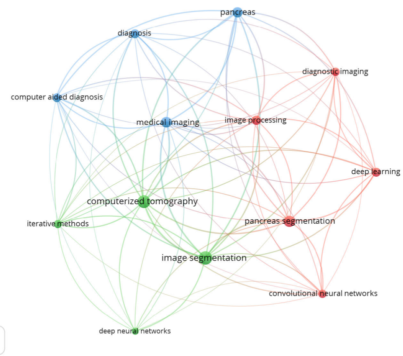

FIGURE 7. Co-occurrence of keywords for pancreas segmentation by VOSviewer.

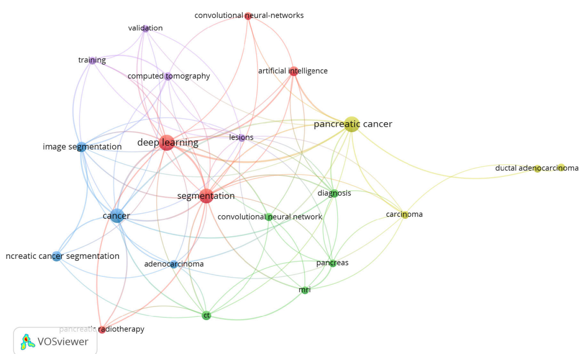

FIGURE 6. Co-occurrence of keywords for pancreatic cancer segmentation by VOSviewer.

consistent upward trend in the number of publications focusing on pancreatic cancer segmentation utilizing artificial intelligence.

B. QUALITATIVE ANALYSIS

Qualitative Analysis includes the co-occurrence analysis that identifies hot topics and aids scholars in better understanding current scientific issues by examining the keywords in a group of publications. In this review, VOSviewer software was used to analyse the co-occurrence of keywords from the Web of Science database. Qualitative analysis was done on both pancreas and pancreatic cancer segmentation. FIGURE 6 represents a visual network map of the co-occurrence of keywords for pancreatic cancer, and FIGURE 7 shows a network map of the co-occurrence of keywords for the pancreas. The visualization nodes are depicted in various colors to represent different clusters. The node size corresponds to the occurrence of keywords associated with it. The greater the size of the node higher the occurrence of keywords. Additionally, a thick connecting line between the nodes indicates a strong relation between the items, highlighting their close association.

IV. IMAGING MODALITIES

Pancreatic cancer diagnosis and evaluation heavily rely on different imaging modalities, each offering unique advantages and capabilities. The common imaging modalities used for the detection, diagnosis, and prognosis of pancreatic cancer are CT, MRI, Positron Emission Tomography (PET) contrast, and enhanced-endoscopy ultrasound (CE-EUS). For the assessment of the pancreas and pancreatic cancer, computed tomography (CT) is frequently used as the primary imaging modality. It provides extensive anatomical information, identifying pancreatic lesions and surrounding structures by exploiting variations in tissue density. The ability to discriminate between healthy pancreatic tissue and tumors based on their vascular characteristics is further improved by enhanced CT. Using CT imaging, the perivascular vascularity around the pancreas may be seen clearly.

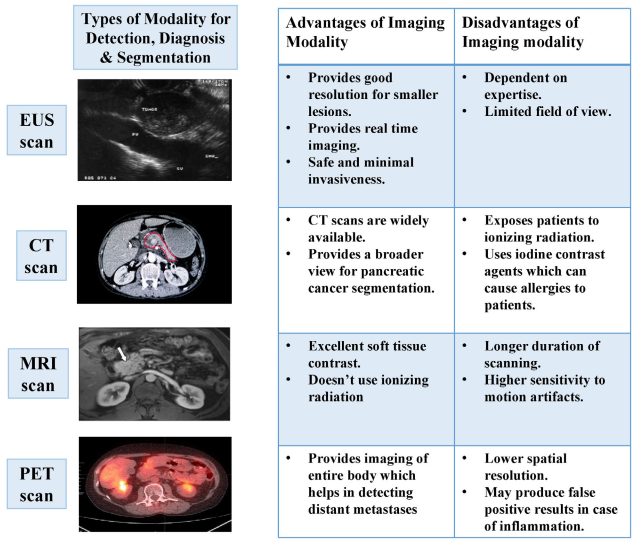

FIGURE 8. Imaging modalities.

Magnetic Resonance Imaging (MRI) is another important modality to observe the pancreas and other organs. MRI scans can help to visualize detailed and in depth properties of organ scans similar to CT. Different imaging sequences can be used by MRI to pinpoint the location of lesions and identify minute anomalies. It is vital to note that CT imaging often provides abdominal imaging with a better degree of precision than MRI.

Another specialized imaging technique, Contrast-enhanced Endoscopy Ultrasound (CE-EUS), is also used as an effective visualization method for pancreas and lesions. In this imaging technique, high-resolution images are taken using an endoscope with an ultrasonic probe that is inserted into the digestive tract. Accurate identification and characterisation of pancreatic tumors are made possible by real-time imaging with good contrast provided by CE-EUS.

Positron Emission Tomography (PET) is another imaging modality that can also be used for pancreatic tumor visualization. A radiotracer that builds up in places with high metabolic activity, such as cancer cells, is injected in this procedure. PET scans are able to locate and identify pancreas and pancreatic tumors, as well as determine the size and likelihood of metastases.

In pancreas and pancreatic cancer evaluation, each modality has its own strengths and weaknesses. There are various factors for the choice of the modality, such as clinical scenario, availability, cost, and expertise. In this literature, the focus will be more on the CT scan modality. FIGURE 8 illustrates different imaging modalities with advantages and disadvantages for pancreas and tumor detection, diagnosis, and segmentation.

V. PANCREAS AND TUMOR SEGMENTATION

The process of medical image segmentation involves utilizing computer-based image processing techniques to extract region of interest from medical images, such as to accurately identify and isolate specific organs, tissues, and tumors from CT and MRI for detection, diagnosis, or for further studies. Segmentation basically divides the image into different sub-regions based on the similarity or differences between regions. Medical image segmentation enables clinicians to examine lesions and other region of interest (ROI) both qualitatively and quantitatively, which can improve the precision of medical diagnosis.

Different automated pancreas and pancreatic tumor segmentation approaches are explained in the literature. The utilization of automated segmentation techniques can alleviate the difficulties associated with manually assessing pancreatic tumors. In this section, first, different pre-processing techniques will be discussed. Next conventional segmentation techniques followed by supervised machine learning and deep learning methods for pancreas segmentation and finally the paper delves into the methods for pancreatic tumor segmentation with their reported performance.

A. PRE-PROCESSING TECHNIQUES TO REMOVE NOISE AND ENHANCE THE IMAGE QUALITY

Pre-processing medical images is crucial before performing any image analysis or segmentation. Pre-processing improves the image quality and helps remove the noise for better outcomes in terms of accuracy and reliability for segmentation tasks. In medical images, noise occurs during acquisition, specifically when there is a low radiation dose. Handling different types of noise is necessary for accurate and precise segmentation of pancreas and pancreatic tumors. Some of the most common noises are salt and pepper noise, Gaussian noise, speckle noise, motion artifacts, etc. Different filtering techniques are incorporated to reduce this noise. Previously, the noise was removed by traditional filtering techniques such as mean, median, Gaussian, and Weiner filters. Nowadays, deep learning based methods such as deep CNN [12], CNN denoising autoencoder [13], Generative Adversarial Networks (GAN) [15], [16], conditional GAN [17], [18], etc. are used to remove noise from medical images. Other pre-processing operations, including intensity normalization, cropping, resizing, and data augmentation techniques, are performed to improve the quality of CT scans. Intensity normalization is standardizing the pixel values such that images should have consistent pixel values for segmentation. Cropping focuses on the region of interest and discards the area outside that region. Resizing helps to change the resolution or spatial dimensions of the CT scans to achieve the desired resolution. Data augmentation helps to increase the training data artificially. Different augmentation techniques, such as rotation, scaling, zooming, and flipping, are applied to improve the robustness of machine learning models for limited training data. The choice of pre-processing should align with the medical imaging modality and segmentation task. Pre-processing plays a vital role in enhancing the quality and effectiveness of medical images. Pre-processing also helps to mitigate issues such as acquisition settings and noise. It is essential to consider pre-processing as an integral component of the medical image segmentation pipeline to achieve good results.

B. AUTOMATIC METHODS FOR PANCREAS SEGMENTATION

1) CONVENTIONAL SEGMENTATION METHODS

In conventional segmentation techniques, the multi-organ atlas-based method is among the common approaches for medical image segmentation. The ''multi-organ'' name indicates that this method segments multiple organs, and the name ''atlas'' indicates a labeled reference image or predefined template of an anatomical structure. The atlas can be the pancreas, liver, spleen, and any other abdominal organ. The atlas is obtained from CT images wherein the organs are manually segmented and labeled, which is further used as a reference for implementing different segmentation algorithms. A pre-existing atlas or template of the pancreas can be used further to guide the segmentation process.

During the segmentation stage, the atlas or template is matched with the target CT scan using image registration techniques. The labeled information is transferred to the associated structures, such as the pancreas in the target image, by registering the atlas with the target image.

The segmentation algorithm can precisely detect and outline the pancreas in the target CT image with the help

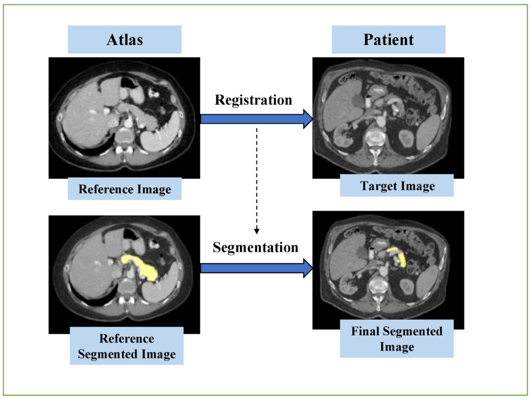

FIGURE 9. Atlas-based segmentation of pancreatic tumor.

of an atlas which provides valuable insights about the shape and location of the pancreas. The algorithm may overcome difficulties seen in CT scans, such as blurred borders and low contrast, by making use of the atlas.

Overall, the use of an atlas in CT image analysis makes it easier to segment anatomical structures automatically by giving a reference template and prior knowledge of the predicted appearance and spatial connections of organs, such as the pancreas. A variety of therapeutic applications, such as the identification and planning of pancreatic cancer, are made possible by this method's improved precision and efficacy in pancreas segmentation in CT scans. The multiorgan atlas-based segmentation method offers the benefit of low training time. The atlas-based segmentation approach is represented in FIGURE 9.

Shen et al. [13] proposed an automated segmentation method for various organs in the abdomen and adipose tissue compartments. Their approach utilized a multi-atlas registration technique, involving the manual creation of 19 atlases, followed by registration-based segmentation. The method was evaluated on data from 26 obese patients pre- and post-weight-loss intervention, demonstrating good agreement with manual segmentation.

In a separate study by Tong et al. [14], a technique for multiple organ segmentation using CT scans was developed. They employed two DDLS (discrimination-based dictionary learning) methods. In the first, called global DDLS (G-DDLS), a set of atlases was chosen depending on how closely they resembled the target image within the global mask. The second, local DDLS (L-DLS), used voxel-wise atlas selection to choose similar atlases locally at various locations inside the target image.

Wolz et al. [15] developed a fully automated multi-organ segmentation that involves a hierarchical atlas generation step and a refinement step. The atlas labels generated during this step are used to describe and define anatomical structures at different scales - global (entire image), organ (individual organ), and voxel level(pixels). The most suitable atlases are selected based on the global image appearance, aligned with the target image, and weighted locally on an individual organ. Subsequently, a patch-based segmentation refinement is performed at the voxel level. To enhance the segmentation, a graph-cuts based refinement step is conducted, incorporating constraints related to local smoothness and high-level spatial relationships.

In order to choose atlases with a high degree of pancreatic similarity to the unlabeled volume, Karasawa et al. [16] implemented a structure specific atlas generation that used structural information in the generation of the atlas. Chu et al. [17] generated probabilistic atlases to segment the pancreas and other abdominal organs using maximum a posterior (MAP) estimation and a graph cut method. Saito et al. [18] use a statistical shape model to consider all possible shapes and a search algorithm to select the best shape for pancreas segmentation. This approach does not require predefined shapes or complex hierarchies. The algorithm optimizes both the shape model and the segmentation labeling, resulting in more precise and efficient segmentation. A regression forest technique was implemented by Oda et al. [19] to evaluate the size of the pancreas, position of the pancreas, and a patient specific atlas generation wherein a new similar atlas was generated based on information related to blood vessel characteristics. The segmentation process employed a combination of the expectation maximization (EM) algorithm, utilizing atlases as priors, and the graph-cut optimization method. The utilization of the multi-organ atlas-based method can significantly enhance the results of pancreas segmentation, playing a vital role in applications like diagnosis and pancreatic cancer treatment.

2) SUPERVISED MACHINE LEARNING & DEEP LEARNING BASED SEGMENTATION OF PANCREAS

Machine learning based techniques are classified into two major techniques supervised and unsupervised learning. Supervised machine learning based pancreas segmentation techniques have recently come to light as potential alternatives to the challenges faced by the traditional segmentation approach. These methods use huge of annotated medical image data to train the models that accurately identify and segment the pancreas. Figure 10 shows the evolution of pancreatic cancer segmentation from the 1950s using machine learning and deep learning.

Deep learning uses multiple layer artificial neural networks (hence "deep") to learn complex patterns and representations directly from the data. The training of the neural network involves a vast collection of labeled medical images, where the ground truth segmentation of the target structures is provided for training purposes. The network learns to autonomously extract pertinent features and patterns from the input image and maps them to their respective segmentation masks. Convolutional neural networks (CNNs) play a pivotal role in deep learning by directly extracting features from the images. Recently deep learning techniques can achieve state-of-the-art results in pancreas segmentation tasks. These methods have the potential to improve the accuracy and

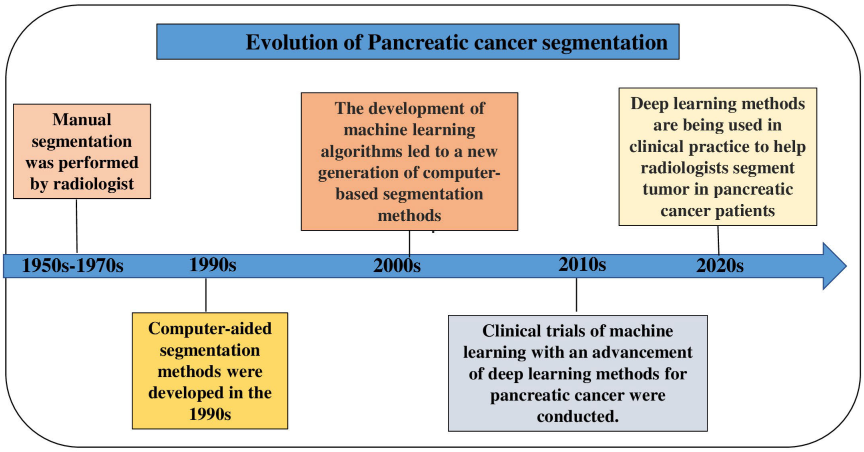

FIGURE 10. Evolution of machine learning and deep learning for pancreatic cancer segmentation.

efficiency of pancreas segmentation, which can lead to better diagnosis, treatment, and patient outcomes. Convolutional neural networks (CNNs) are widely employed to segment the pancreas, due to their effective learning characteristics that allow them to directly learn from imaging data. Several CNN-based techniques like deep CNNs [20], VoxResNet [21], SegNet [22], fully convolutional neural networks (FCNs) [23], and U-Net [24] have shown promising results in performing pixel-level labeling tasks for semantic segmentation. These algorithms employ different architectures and techniques such as skip connections, pooling, and upsampling, to increase the segmentation accuracy and efficiency. For instance, the U-Net employs a contracting path and an expanding path for feature extraction and localization. The VoxResNet architecture combines residual learning with a 3D CNN to capture both spatial and temporal information.

Zhou et al. [25] proposed a "coarse to fine" model for pancreas segmentation that involves the use of a coarse-scaled and fine-scaled network. The framework is built upon the observation that processing smaller input regions can achieve more precise segmentation outcomes. Despite being trained and tested independently, this approach has been shown to deliver better accuracy.

Additionally, they showcased a saliency transformation network [26], which includes the generation of spatial weights using the score map obtained from the coarse-scaled segmentation network and applying these weights to the fine-scaled segmentation network. This method allows both segmentation networks to be adjusted together, making them more efficient.

The holistically nested network, initially developed for edge detection using deep learning, was repurposed for image segmentation and showed promising results in pancreatic segmentation [27], [28]. It uses deep dense per pixel masking to process different sequences of 2D image slices. However, it did not explore explicitly applying a spatial consistency requirement on slice segmentation.

Zhu et al. [29] implemented a ResNet architecture on 3D data for segmentation of the pancreas. This framework takes advantage of extensive spatial information and all three dimensions of data, leading to better segmentation results than the 2D counterpart.

Roth et al. [30] implemented a cascaded dual stage architecture that consists of pancreas localization and segmentation. In the first stage, the pancreas is localized, and a robust bounding box is produced for more comprehensive segmentation in the second stage. To segment the pancreatic tissue, a holistically nested convolutional network (HCNN) is used, which takes into account three orthogonal views: coronal, axial, and sagittal. The HCNN combines multiple convolutional layers to capture multi-scale features, which leads to improved segmentation results. Pooling is used to concatenate the HCNN probability maps for every pixel, which helps to generate a 3D bounding box of the pancreas and improve recall. This approach is advantageous since it reduces the likelihood of missing any part of the pancreas during segmentation, which can be critical for the detection of pancreatic diseases.

Attention U-Net was proposed by Oktay et al. [31] for pancreas segmentation. The model combines the attention mechanism and U-Net architecture to selectively highlight regions of the input image that are relevant for pancreas segmentation. This attention mechanism is learned from the input image itself, which allows to focus on informative regions and suppress irrelevant regions. The Attention U-Net comprises an encoder and decoder layer with skip connections between them. The attention mechanism is added in the decoder part of the network, where it performs element-wise multiplication of the generated spatial attention maps with the feature maps from the encoder layers. These attention maps are learned by the model during training to highlight the relevant features for pancreas segmentation. On two distinct datasets, the model was assessed and achieved an exceptional outcome. A detailed analysis of the attention

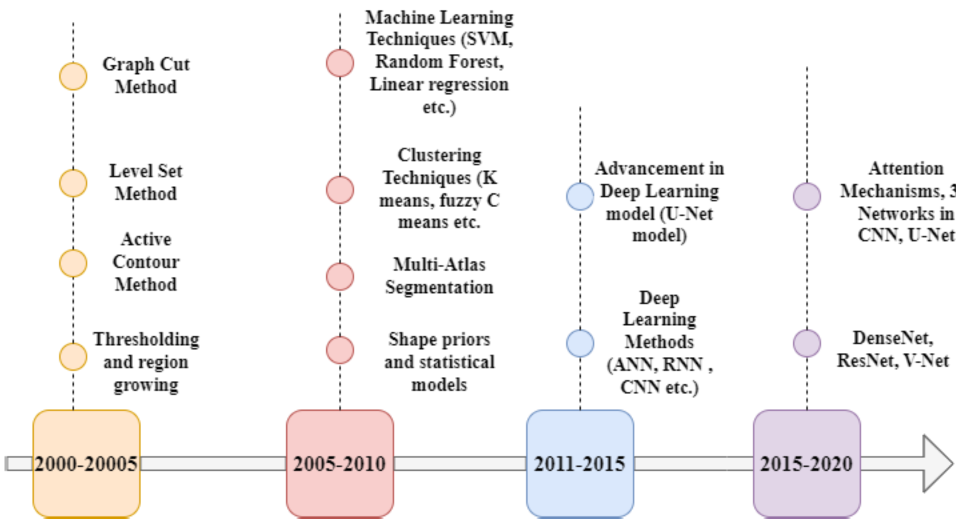

FIGURE 11. History of different pancreas and pancreatic tumor segmentation methods.

maps was performed, showing that the model indeed learns to focus on the pancreas region and suppress irrelevant background regions.

For pancreas segmentation, Man et al. [32] introduced a novel approach based on deep reinforcement learning in CT images using a geometry-aware deformable U-Net. Their approach involves a two-stage process, with the first stage focusing on, a single slice of the 3D CT volume is selected, and a reinforcement learning agent is trained to identify the optimal bounding box for the pancreas in that slice. In the second stage, the identified pancreas region is segmented using the deformable U-Net, which utilizes the shape information of the pancreas in different slices. The pixel-wise results from the three orthogonal axes (coronal, axial, and sagittal) are combined to generate the final segmentation. Their approach demonstrated superior performance compared to other existing methods for pancreas segmentation.

Xue et al. [33] developed a method of two cascaded phases, where the first phase localizes the pancreatic region using a shape-specific module that extracts shape-specific features from the CT image. For precise pancreas segmentation, the second phase uses a multitask 3D dense-U-Net. The proposed method surpasses various advanced techniques, such as U-Net, Attention U-Net, and Shape-aware U-Net, in terms of segmentation performance and handles inter-slice inconsistencies using a slice-to-slice fusion mechanism. The suggested strategy is effective and accurate for the clinical use of pancreas segmentation.

Farag et al. [34] introduced a novel bottom-up approach for segmenting the pancreas consisting of two main stages. In the first stage, the authors proposed a superpixel-based segmentation method to generate an initial segmentation mask, which is then refined using a cascaded framework. In the second stage, the authors proposed a deep image patch labeling method to classify each image patch as pancreas or non-pancreas using a deep CNN.

Chen et al. [35] presented a method that incorporates a multi-scale supervision approach and two-view feature learning for pancreas segmentation using CT images. The method effectively captures the multi-view complementary information of the pancreas and combines features at different scales to improve the segmentation accuracy.

A MobileNet-U-Net (MBU-Net) is proposed by fusing MobileNet-V2 and U-Net architecture with repetitive dilated convolutions for semantic pancreas segmentation [36].

Qiu et al. [37] introduced a novel framework called dual enhancement module, that enhances fine-scale segmentation input from the coarse-scaled segmentation mask. Segmentation performance was improved using multi-scale feature calibration U-Net (MFCUNet) architecture at the pixel level, as directly fusing these features for recovering boundary information can lead to redundancy and inaccuracies. Additionally, a cascaded MFCUNet was implemented, that combines the merits of both MFCUNet and dual enhancement module, achieving the best pancreatic segmentation performance possible. Overall, the proposed framework demonstrates significant improvements in pancreatic segmentation using medical images. He et al. [38] developed a model combining U-Net with a transformer called U-Netmer for the segmentation of medical images. The U-Netmer model offers flexibility in segmenting input images with various patch sizes while maintaining the same structure and parameters. This unique design and clever training strategies enable the U-Netmer to effectively integrate multi-scale contextual knowledge during the learning process.

Wang et al. [39] implemented a two input approach for pancreas segmentation, which includes a graph based visual saliency (GBVS) algorithm and a v-mesh FCN which helps to enhance feature extraction and reduces the semantic gap, an attention mechanism combines multiple feature maps to emphasize ROIs.

Li et al. [40] implemented a probabilistic-map-guided bi-directional recurrent UNet (PBR-UNet) for the segmentation of the pancreas. It combines intra-slice information and inter-slice probabilistic maps to create a local 3D hybrid regularization strategy, and a bi-directional recurrent optimization scheme is followed to improve the accuracy.

Quereshi et al. [41] implemented a multiphase deep learning framework for precise pancreatic segmentation in CT imaging. The pancreas is localised using the VGG-19 deep learning network, and then soft labels are created in the localised area. A 3D volume template that depicts the overall form of the pancreas is then combined with the soft labels. This fusion process allows for the refinement of soft labels and leads to improved segmentation results.

Giddwani et al. [42] proposed a multi-rate deep dilated V-Net architecture, which demonstrated better segmentation performance. Mo et al. [43] developed a 3D iterative enhancement network that accurately segmented the pancreas. They used a residual network for feature extraction and refined individual features. Nishio et al. [44] used standard and deep U-Nets for the segmentation of the pancreas. Zhu et al. [45] integrated a neural architecture search to find the optimal architecture between 2D, 3D, or pseudo 3D convolution at each layer. They implemented neural architecture search on NIH and MSD dataset.

Fan et al. [46] implemented a regularized U-Net architecture to achieve regularized pancreas segmentation. Similarly, other U-Net architectures, such as fully-convolutional U-Net [47], attention U-Net [31], and automatic multi-organ segmentation with adversarial loss [48], have been developed to achieve better segmentation results. Dai et al. [49] developed a Trans-Deformer network using a combination of 2D U-Net at the coarse stage and added a deformable convolution to the vision transformer at the fine stage. They implemented the architecture on both the NIH and MSD datasets. Thus application of supervised machine learning and deep learning based algorithms is widely implemented for the segmentation of the pancreas.

3) UNSUPERVISED MACHINE LEARNING BASED SEGMENTATION

Unsupervised machine learning is the algorithm that learns patterns and structures from unlabeled data without explicit guidance or supervision. Examples of unsupervised learning methods consist of K-means clustering [50], Principal Component Analysis (PCA) [51], and Non-negative Matrix Factorization (NMF) [52]. Very few papers represent the segmentation of the pancreas and tumor using unsupervised learning. Roy et al. [53] used an improved K-means clustering for tumor segmentation. Jain et al. [54] developed an unsupervised approach that localizes the pancreas from CT scans. Clustering-based methods evaluate the clustering quality using the Clustering Validity Index (CVI). The clustering index helps researchers to assess and compare different clustering algorithms. There are different types of CVIs, such as the Davies-Bouldin Index, Silhouette Score, Dunn Index, etc. Tang et al. [55] developed a novel CVI called the Triple Center Relation (TCR) index for fuzzy clustering. It considers two factors, within-class compactness and between-class separateness, which is a vital property of the TCR index. This index is robust and can achieve good results for high-dimensional datasets. The application of unsupervised learning techniques is uncommon in pancreas and pancreatic tumor segmentation research.

C. DEEP LEARNING BASED SEGMENTATION OF PANCREATIC TUMOR

Segmentation of pancreatic tumor and cyst is quite challenging as compared to segmentation on the pancreas. Deep learning has become a popular technique for pancreatic tumor segmentation due to its ability to automatically extract intricate patterns and features from extensive datasets. Figure 11 shows the overall history of different pancreas and pancreatic tumor segmentation methods. A detailed illustration of machine learning and deep learning based segmentation is represented in Figure 12. This section presents a review of various methods used for pancreatic tumor segmentation.

Du et al. [56] implemented a novel multi-scale channel attention UNet architecture to segment pancreatic tumor. The multi-scale network was embedded into the encoder and decoder for semantic information extraction. This work was implemented on the private dataset and focused on segmenting small pancreatic tumors.

Li et al. [57] performed the segmentation with a 3D FCN. To enhance tumor segmentation without compromising the pancreatic information, they employed three different guided modules for temperature. The balancing temperature loss function was created with the specific purpose of dynamically adjusting the learning points between the pancreas and the tumor, ensuring a balanced selection of features. Additionally, they implemented a rigid temperature optimizer to probabilistically accept non-improving movements and adaptively avoid local optima. Furthermore, they incorporated a soft temperature indicator that automatically guided the network towards a fine-tuning phase as the model reached stability. This approach led to improved segmentation outcomes, ensuring both accuracy and efficiency in jointly segmenting the pancreas and pancreatic tumors. Overall, their methodology showcased promising results in this regard.

Zhu et al. [58] introduced a framework that combines segmentation and classification for interpreting abnormality in medical images. The framework involves training a segmentation network to identify tumor voxels and then performing classification based on the presence of these voxels in testing volumes. Two important techniques were employed to enhance classification accuracy: multi-scale network training and coarse-to-fine testing. Significantly,

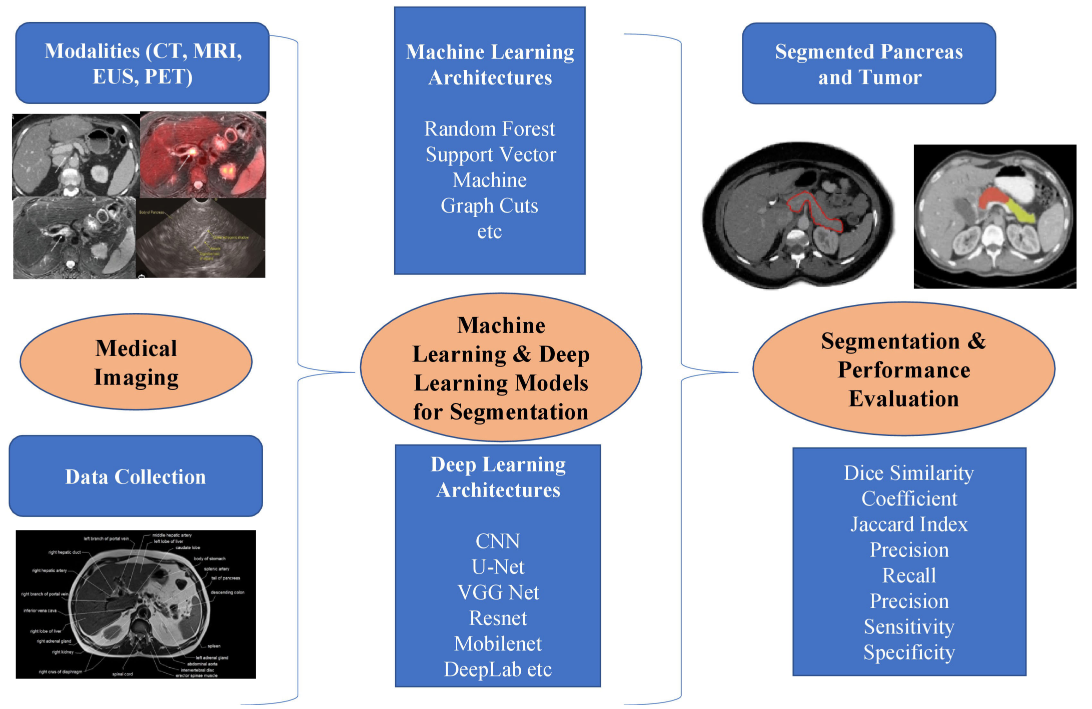

FIGURE 12. Illustration of machine learning and deep learning-based segmentation techniques.

these strategies helped the classification process perform better overall.

Chen et al. [59] developed a novel approach unified tumor Transformer (UniT) model for the simultaneous diagnosis, detection, and segmentation of eight common cancers from 3D CT scans. UniT leverages a query-based transformer architecture and introduces a clinically inspired hierarchical tumor representation. It incorporates a dual-task query decoding stage to generate segmentation masks. Oh et al. [60] introduced a method for the segmentation of pancreatic cystic lesions from endoscopic ultrasonography (EUS) images. They developed an attention U-Net architecture, which incorporates an attention mechanism that enables concentrating on the informative regions of input images. This architecture was assessed on both internal and external test datasets and a comparison with other cutting-edge models like Basic U-Net, Residual U-Net, and U-Net++.

Alves et al. [61] developed a nn-UNet for the detection and segmentation of pancreas and pancreatic tumor. This architecture is an extension of the 3D U-Net model which also includes a deep supervision mechanism to enable better training of the network. The nn-UNet architecture achieved better performance for the pancreas and showcased better results for tumor detection. This architecture is capable of simultaneously segmenting multiple anatomical structures.

Si et al. [62] segmented pancreatic tumor using a combination of three different architectures. The pancreas was detected using ResNet-18, and U-Net32 was used for the segmentation of the pancreas region from the CT scan. Finally, ResNet-34 was implemented for tumor detection. This approach demonstrated better accuracy for both pancreas and tumor detection.

Mahmoudi et al. [63] developed a framework for pancreas and tumor segmentation by combining the CNN architecture with textured U-Net architecture. Initially, the pancreas was localized by CNN and then segmentation of tumor was performed using textured U-Net architecture. The framework showed better results for the pancreas than the pancreatic tumor segmentation.

Iwasa et al. [64] presented an automated system for the segmentation of PDAC from contrast-enhanced endoscopic ultrasound (CE-EUS) video images. The system utilized a U-Net and performed training and evaluation using a 4-fold cross-validation. This method showed good results in segmenting PDAC from CE-EUS images and has the potential to aid in the early diagnosis and treatment of PDAC. Li et al. [65] introduced an enhanced UNet framework called Position Guided Deformable UNet (PGDUNet) architecture. With regard to tumor segmentation, this architecture handles issues including size and form variations and significant class imbalance. PGDUNet consists of a deformable convolution with a localization route and a focal loss function for the suppression of noise. The study specifically focuses on both the pancreas and pancreatic tumor segmentation.

Tureckova et al. [66] developed a novel approach to improve the accuracy of pancreatic tumor segmentation. Deep supervision and attentional gates were used in their network architecture to enhance the segmentation accuracy.

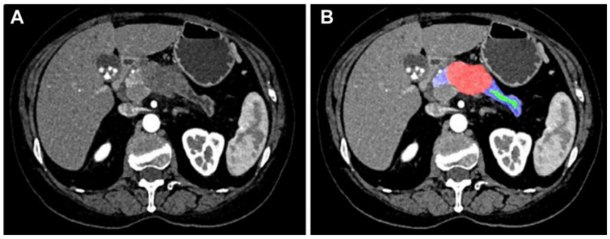

FIGURE 13. Example of abdominal CT scan of the pancreas and PDAC segmentation. (A) A non-segmented CT scan of the abdomen (B) Segmented pancreas in blue, tumor in red, and duct in green colour [69].

The use of attentional gates helped to focus on the vital regions, while deep supervision helped in better training of the network.

Jiang et al. [67] implemented DLU-Net for the segmentation of pancreatic tumor edges. The model is proposed of a densely connected U-Net architecture combined with an attention gate module and deep supervision mechanism. The proposed method can assist clinicians in more accurate tumor segmentation and treatment planning.

Liang et al. [68] developed an automated system for pancreatic tumor segmentation using multi-parametric MRI scans. The system consists of three different modules: feature extraction, classification, and segmentation. This system was implemented on a private dataset giving better results for the segmentation of tumor. The sample abdominal CT scan of the pancreas and pancreatic tumor segmentation is represented in FIGURE 13.

Zheng et al. [70] developed a framework for the segmentation of the pancreas using a squeeze and extraction block in U-Net architecture. The uncertain regions were also determined using shadowed sets. The framework was implemented using MRI as well as CT scans. The MRI dataset was used to segment the tumor and the CT scan dataset segmented the pancreas. This makes the framework versatile in clinical practice.

Guo et al. [71] segmented pancreatic tumor using combination of U-Net and Layered Optimal Graph Image Segmentation for Multiple Objects and Surfaces (LOGISMOS) approach. The LOGISMOS approach incorporates the geometric and spatial information in the segmentation. The graph-based approach of LOGISMOS helps user to adjust the segmentation by changing nodes and edges. This method enables to precisely segment pancreatic tumor.

Zhou et al. [72] implemented Deep FCN for segmentation of pancreas and cyst. This method was implemented on private dataset of 131 CT scans. Deep FCN approach demonstrated better results for pancreas segmentation and quite good results for segmentation of cyst.

Thus precise and reliable segmentation of pancreatic tumor is achieved using deep learning techniques. Table 3 summarizes the various deep learning based methods and its performance for pancreatic tumor and cyst segmentation. The majority methods have been evaluated on publicly available as well as privately available datasets, demonstrating their potential for clinical applications. Furthermore, the advancement of deep learning-based segmentation techniques has revolutionized the segmentation process by automating it, thereby minimizing the requirement for manual intervention. This automation facilitates early detection and treatment of pancreatic cancer, offering significant benefits in terms of timely medical interventions.

VI. EVALUATION METRICS

The evaluation of segmentation techniques typically involves comparing the results obtained from the model with the ground truth segmentation obtained through manual annotations. The performance is evaluated using different evaluation metrics. The most commonly used metrics are the Dice similarity coefficient (DSC) and the Jaccard index (JI). DSC and JI [44], [70], [72], [73] are the similarity metrics that measures the similarity between ground truth and predicted segmentation results. DSC is defined in equation 1 as:

$$DSC = \frac{2 * |A \cap B|}{|A| + |B|} \tag{1}$$

Jaccard Index is defined in equation 2 as:

$$JI = \frac{|A \cap B|}{|A \cup B|} \tag{2}$$

where A and B represent the ground truth mask and the predicted mask, respectively. The numerator represents the number of pixels that are correctly segmented in both the ground truth and predicted masks, while the denominator denotes the cumulative pixel count in both masks. Both DSC and JI range from 0 to 1, with a value of 1 indicating perfect segmentation accuracy or resemblance in the ground truth and predicted masks. A low value of either metric indicates that the predicted mask is significantly different from the ground truth mask.

Accuracy [67] and [70] is also widely utilized for deep learning-based segmentation techniques. It measures the overall correctness of the segmentation results by calculating the proportion of correct pixels classified in the predicted segmentation. Accuracy is represented in equation 3

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

where TP (true positives) represents the count of pixels correctly classified as positive, TN (true negatives) represents the count of pixels correctly classified as negative, FP (false positives) represents the count of pixels incorrectly classified as positive, and FN (false negatives) represents the count of pixels incorrectly classified as negative.

Sensitivity (SI) or true positive rate (TPR) or recall [39], [60], is an evaluation metric used to measure the ability of a deep learning-based segmentation model to correctly detect positive samples. In the context of segmentation, positive samples refer to pixels or regions that belong to the target structure being segmented. Sensitivity is defined in equation 4 as:

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

Sensitivity ranges from 0 and 1, where 1 indicates the detection of all positive samples. A low sensitivity value indicates that the model is missing a significant number of positive samples, which can result in incomplete or inaccurate segmentation.

Specificity (SP) [45], [60] measures the ability of a segmentation model to correctly identify negative samples, which are samples that do not belong to the target structure being segmented. Equation 5 represents specificity as:

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Specificity lies between 0 and 1, the 1 represents the identification of all negative samples. A low specificity value indicates that the model is misclassifying a significant number of negative samples as positive, which can result in incomplete or inaccurate segmentation.

Precision measures the accuracy of a segmentation model in correctly identifying positive samples, which are samples that belong to the target structure being segmented. Precision is defined in equation 6 as:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Higher the value of accuracy, precision, and recall, the better the segmentation results [40], [73]. Hausdorff distance measures the accuracy of segmentation by calculating the maximum distance between the boundary points of the ground truth and predicted segmentation masks. A smaller Hausdorff distance indicates better segmentation accuracy, as it means that the boundary points of the predicted segmentation are near to those of the ground truth [68]. In pancreatic edge segmentation, for example, a smaller Hausdorff distance indicates better accuracy of the segmented pancreatic margin, as the predicted boundary points are closer to those of the ground truth. The Hausdorff distance is a valuable evaluation metric to complement other commonly used metrics such as DSC, Jaccard Index.

Area under the receiver operating characteristics curve (AUC) is used to evaluate the segmentation model by measuring its ability to differentiate between healthy and tumor tissues in medical images. The AUC is calculated as the area under the ROC curve, which plots the TPR against the FPR at different threshold values. A higher AUC value indicates better performance of the segmentation model [5].

The example of segmentation of the pancreas and PDAC mass is shown in FIGURE 14 with various DSC findings.

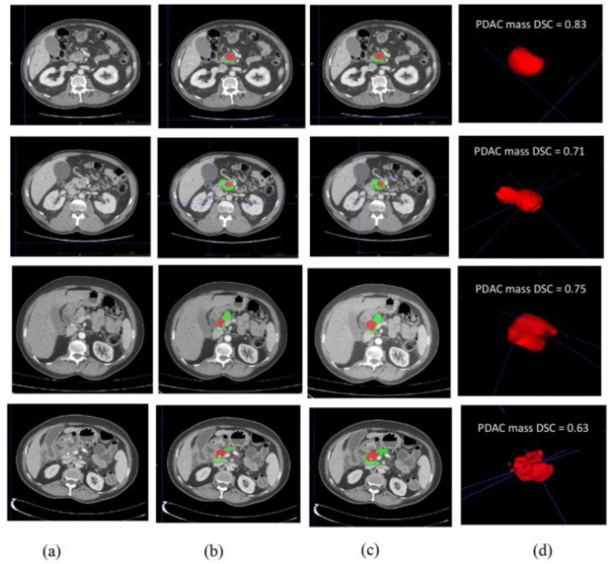

FIGURE 14. Segmentation of PDAC and pancreas (a) Original CT image of different patients (b)Ground Truth (red denotes PDAC and green denotes pancreas) (c) Segmentation output (d) Visualization of PDAC in 3D with DSC value for various patients [63].

VII. EXPERIMENTAL DATASET

In pancreas and tumor segmentation, there is a limited availability of publicly accessible datasets. National Institutes of Health - The Cancer Imaging Archive (NIH-TCIA) dataset [74] is widely recognized as the most commonly used dataset for segmentation of the pancreas as it contains a sufficient amount of labeled data. This dataset comprises 82 CT images with contrast enhancement, each with a resolution of 512 × 512 pixels. The slice thicknesses vary between 1.5 to 2.5 mm. The CT scans were acquired using multi-detector computed tomography (MDCT) scanners from Philips and Siemens, with a tube voltage of 120 kVp.

Another dataset from John Hopkins Medical Institutions (JHMI) [72] comprises 131 abdominal CT volumes with contrast enhancement, and each volume contains annotated pancreatic labels generated by human experts. The CT volumes in the JHMI dataset have a resolution of 512 × 512 pixels in the transverse plane, while the axial plane thickness, denoted as D, varies between 358 and 1121, providing a wider range of slice thickness compared to the NIH dataset.

Another widely used dataset for pancreatic tumor segmentation is the Medical Segmentation Decathlon (MSD) challenge dataset, that comprises of 420 CT scans of portal-venous phase patients with pancreatic tumors acquired from Memorial Sloan Kettering Cancer Center, New York, US.

There are also several private datasets used within institutions, but publicly available datasets are crucial for the researchers to evaluate the benefits and drawbacks of various segmentation methods. Comparing the performance of various methods using a similar dataset is more meaningful for the research community.

VIII. DISCUSSION

In this contemporary review, various pancreas and pancreatic tumor segmentation techniques are explored. Deep learning methods have emerged as a popular and promising approach, demonstrating superior performance in accurately segmenting the pancreas and pancreatic tumors than conventional segmentation methods. These methods leverage the power of neural networks to learn intricate patterns and features from large datasets, enabling them to capture complex anatomical structures and subtle tumor boundaries. The evaluation of segmentation performance varies across studies, with different metrics and benchmarks used for assessment.

Several segmentation techniques have been proposed for segmenting the pancreas into distinct groups, catering to different applications and imaging modalities.

The approaches for assessing segmentation performance varies in different ways. DSC parameter and Jaccard Index are largely adopted metrics to measure segmentation accuracy. In the realm of pancreas segmentation, atlas based method by Karasawa et al. [16] demonstrated superior results in terms of Dice Similarity Coefficient and Jaccard Index when compared to conventional multi-organ atlas-based segmentation methods. Their study utilized a dataset comprising 150 CT scans obtained from Nagoya University Hospital. Table 1 represents conventional multi-organ atlas based segmentation methods.

However, recent advancements are particularly utilizing supervised machine learning and deep learning approaches such as U-Net and hybrid architectures, have achieved remarkable results for both pancreas and tumor segmentation. Many of these methods have achieved DSC values exceeding 80%. Table 2 shows the various pancreas segmentation methods and their performance using supervised machine learning and deep learning.

Noteworthy achievements include the U-Net with Trans-Deformer network proposed by Dai et al. [49], which achieved remarkable DSC results of 89.89% for the NIH dataset and 91% for the MSD challenge dataset for pancreas segmentation. The other method multi-phase morphology-guided deep learning framework by Qureshi et al. [41], also which achieved a remarkable DSC of approximately 88.53%. Qiu et al. [37] demonstrated significant improvements in the Jaccard Index (JI) with a value of $76.26 \pm 5.01\%$ for pancreas segmentation, achieving better segmentation results for precision and recall as well.

The MBU-Net architecture [36] showcased exceptional precision $89.29 \pm 0.98\%$ and specificity $99.95 \pm 0.01\%$. Man et al. [32] employed deep Q learning and deformable U-Net, resulting in a higher recall of $86.93 \pm 4.88\%$. The V-Net architecture [42], achieving notable sensitivity 87.70% and precision 97.07%. Table 3 focuses on various deep learning based segmentation methods for pancreatic tumor and cyst. Few methods have performed both pancreas and pancreatic tumor/cyst segmentation [57], [58], [63], [65], [66], [72].

It is imperative for future research to standardize evaluation protocols and compare various segmentation methods using diverse datasets, ultimately advancing the field of pancreas and pancreatic tumor segmentation. However, it is worth noting the challenges in comparing pancreatic tumor segmentation methods, as achieving high DSC values on private datasets is feasible, but researchers face difficulties in achieving comparable results on the MSD challenge dataset.

In a recent study by Du et al. [56], they achieved a noteworthy DSC of 68.03% for pancreatic tumor segmentation on a private dataset focusing on small size tumor. Mahmoudi et al. [63] achieved a DSC of about 60. 6% on the MSD challenge dataset. Furthermore, Alves et al. [61] focused on tumor sizes smaller than 2cm obtaining better results for Area Under the Curve (AUC) about 0. 876. The scarcity of labeled pancreatic tumor datasets has impeded the development of segmentation techniques, leading many researchers to rely on privately available datasets and the MSD challenge dataset for their studies.

In general, there has been a notable improvement in the accuracy assessment of pancreas segmentation methods. However, there remains significant variation in evaluation criteria, and datasets used across different research articles, leading to a lack of consistency. Deep learning methods have gained substantial popularity in pancreas segmentation research, while research specifically focused on pancreatic

TABLE 1. Conventional pancreas segmentation methods.

Author	Modality	Method	Dataset	Results
Chen et al. , 2016	CT	Image registration with label fusion method	40 MRI scans	*DSC*=67.2±15.5%
Karasawa et al. , 2017	CT	Atlas selection based on vessel structure	150 CT scans from Nagoya University Hospital	DSC= 76.3 ± 16.4%, JI= 63.9 ± 17.1%
Saito et al. , 2016	CT	Joint optimization algorithm	140 CT scans	DSC= 74.4 ± 20.2%, JI= 62.3 ± 19.5
Oda et al. [19], 2016	CT	EM algorithm with graph-cut optimization	147 CT scans	Dice overlap= 75.1 ± 15.4%, JI= 62.1±16.6%
Tong et al. , [14], 2015	CT	DDLS Algorithm	150 CT scans from Nagoya University Hospital	DSC= 65.5 ± 17.8%
Wolz et al. [15], 2013	CT	Hierarchical atlas registration integrated with weighting scheme	150 CT scans from Nagoya University Hospital	DSC= 69.6 ± 16.7%, JI= 55.5 ± 17.1%, Recall = 67.9 ± 18.2%, Pr = 74.1 ± 17.1%
Chu et al. [17], 2013	CT	Spatially divided probabilisitc atlases	100 CT scans	DSC = 69.1 ± 15.3%, JI = 54.6%

TABLE 2. Pancreas segmentation methods using supervised machine learning and deep learning.

Author	Modality	Method	Dataset	Results
Dai [49], 2023	CT	Trans-Deformer Network	NIH TCIA pancreas dataset & MSD challenge dataset	NIH TCIA pancreas dataset DSC=89.89 ± 1.82%, MSD challenge dataset DSC= 91.22 ± 1.37%
Qiu [37], 2023	CT	Cascaded multiscale feature calibration U-Net (CMFCUNet)	NIH TCIA pancreas dataset	DSC = 86.30±4.03%, JI = 76.26±5.01%, Pr= 85.91±3.97%, Recall= 86.85±5.23%
He et al. [38], 2023	CT	U-Netmer	MSD Challenge dataset	DSC = 79.42 ± 7.59%, JI = 66.46 ± 9.63%, Accuracy=99.47 ± 0.23%, SI= 78.49 ± 11.77%, SP=99.78 ± 0.11%
Quereshi [41], 2022	CT	VGG net& U-Net	NIH TCIA pancreas dataset	DSC = 88.53%
Haipeng Chen [35], 2022	CT	TVMS-Net	NIH TCIA pancreas dataset & MSD challenge dataset	NIH TCIA pancreas dataset- DSC=85.19 ± 4.73%, Pr=86.09 ± 5.93%, Recall=84.58 ± 8.09% IOU=74.19 ± 7.27% & MSD Challenge dataset- DSC=76.6 ± 7.3%, Pr=87.7 ± 8.3%, Recall=69.2 ± 12.8%, IOU=62.6 ± 9.3%
Mei-Ling Huang [36], 2022	CT	MBU-Net (Mobile U-Net)	NIH TCIA pancreas dataset	DSC=82.87 ± 1.00%, JI=70.97 ± 1.39%, Pr=89.29 ± 0.98%, SP=99.95 ± 0.01%, Recall=77.37 ± 1.41%
Moritz Knolle [75], 2021	CT	MoNet	MSD challenge Dataset and independent validation set (IVD)	Dice Score for MSD dataset= 78±9.0% Hausdorff Distance for MSD dataset = 1.78±0.61mm, Dice Score for IVD Dataset 70± 10%
Yuan Wang [39], 2021	CT	V-mesh network	NIH TCIA pancreas dataset	DSC=87.4 ± 6.8%, SI=87.7 ± 7.9%
Jun Li [40], 2021	CT	PBR-UNet	NIH TCIA pancreas dataset	DSC=84.19 ± 5.73%, HD=3.19 ± 0.40 mm, RMSE=3.60 ± 2.57 mm, Recall=82.23 ± 9.14%, Pr=81.44 ± 7.53%, IOU= 72.62 ± 9.09%
T. G. W. Boers [76], 2020	CT	3D interactive U-NET	Private Dataset	DSC=78.1±8.7%
Bharat Giddwani [42], 2020	CT	V-NET	NIH TCIA pancreas dataset	DSC=83.31%, SI=87.70%, Pr=97.07%
Juan Mo [43], 2020	CT	CNN	NIH TCIA pancreas dataset	DSC=82.47±5.50%
Mizuho Nishio [44], 2020	CT	Deep U-Net	NIH TCIA pancreas dataset	DSC=78.9 ± 8.3%, JI=65.8 ± 10.3%, SI=76.2 ± 12%, SP=1.000 ± 0%
Zhuotun Zhu [45], 2019	CT	Neural architecture search	NIH TCIA pancreas dataset & MSD challenge dataset	For NIH dataset: pancreas DSC= 85.15 ± 4.55%, For MSD challenge: pancreas DSC= 79.94 ± 8.85%
JIA Fan [46], 2019	CT	Regularized U-Net (RUNet)	NIH TCIA pancreas dataset	Accuracy= 99.43%, mean intersection over union (mIoU)= 75.73, DSC= 68.45%
Ningning Zhao [47], 2019	CT	U-Net	NIH TCIA pancreas dataset	DSC=84.10 ± 4.91%, JI=72.86 ± 6.89% , Pr=83.60±5.85%, Recall=85.33±8.24%
S. Liu [48], 2019	CT	U-Net	NIH TCIA pancreas dataset	DSC=84.10 ± 4.91%, JI=72.86 ± 6.89% , Pr=83.60±5.85%, Recall 85.33±8.24%
Man [32], 2019	CT	Deep Q Learning & deformable U-Net	NIH TCIA pancreas dataset	DSC= 86.93 ± 4.92%, Recall=86.91 ± 4.88%
Xue [33], 2019	CT	3D FCN	NIH TCIA pancreas dataset & Fujian Medical University dataset	For NIH TCIA dataset DSC = 85.9 ± 5.1%, JI = 75.7 ± 7.6%, Pr = 87.6 ± 4.7%, Recall = 85.2 ± 8.9%
Oktay [31], 2018	CT	Attention gate model with U-NET	NIH TCIA pancreas dataset	DSC=83.1 ± 3.8%, Pr=82.5 ± 7.3%, Recall=84.0 ± 5.3%
Roth et al. [30], 2018	CT	Spatial aggregation using random forest	NIH TCIA pancreas dataset	DSC=81.27 ± 6.27%
Zhu et al. [29], 2018	CT	ResDSN Coarse to Fine model	NIH TCIA pancreas dataset	DSC=83.18 ± 6.02%
Yu et al. [26], 2018	CT	Reccurent saliency Transformation Network	NIH TCIA pancreas dataset	DSC=84.50 ± 4.97%
Zhou et al. [25], 2017	CT	Coarse to fine segmentation	NIH TCIA dataset	DSC= 82.37 ± 5.68%
MinFu [73], 2016	CT	Richer convolutional features network (RCF)	Private dataset from General Surgery Department of Peking Union Medical College Hospital	DSC=76.36 ± 17.96%, Pr=77.36 ± 17.96%, Recall= 79.12 ± 16.27%, JI=63.72 ± 17.05%

TABLE 3. Pancreatic tumor and cyst segmentation methods.

Author	Modality	Method	Dataset	Results
Du et al. [56], 2023	CT	Multi-scale channel attention U-Net	CT images of 419 patients from affiliated Hospital of Qingdao University	DSC= 68.03% & Jaccard Index= 59.31%
Qi Li et al. [57], 2023	CT	3D FCN	MSD challenge dataset	For pancreas: DSC= 85.06±7.71% , For Tumor: DSC= 59.16±28.12%
Chen et al. [59], 2023	CT	Unified Tumor Transformer (UniT) model	Shengjing Hospital of China Medical University	DSC = 70.2%
Seak Oh et al. [60], 2022	endoscopic ultrasound (EUS)	Attention U-Net	EUS Dataset A- 52 patients with 57 images from the Gil Medical Center & EUS Dataset B- 59 patients with 364 images from the Severance Hospital	Dataset A- Accuracy= 98.3± 1.2%, SP=99.1 ± 0.9%, SI=79.7±32.7%, DSC=79.4±32.6%, IOU=7.41(0.308) & Dataset B- Accuracy=97.2±3.7%, SP=98.9±1.4%, SI=72.3±32.2%, DSC=69.1±28.3%, IOU=58.7±27.6%
Natalia Alves et al. [61], 2022	CT	nn-UNet	MSD Challenge Dataset	AUC= 0.914 of the entire external test set and AUC= 0.876 for the tumors less than 2 cm in size
Ke Si et al. [62], 2021	CT	RESNET & U-NET	319 patients from Zhejiang University School of Medicine, China with 143,945 dynamic CT images of the abdomen	AUC=0.871, and Accuracy of PDAC=87.6, Accuracy of IPMN=100%, Accuracy of SCN=81.3%, Average accuracy=82.7% on an independent testing dataset of 347 patient. Computation time =18.6 s per patient
Tahereh Mahmoudi et al. [63], 2021	CT	Texture attention U-Net(TAU-Net)	MSD challenge dataset	For pancreas: Dice Global=72.7%, Dice per Case= 73.8± 8%, Recall= 70.9±21%, Pr= 70.1± 1%, For PDAC mass: Dice Global =60.6%, Dice per case=57.3±15%, Recall= 78.0±9%, Pr= 57.8±23%
Yuhei Iwasa et al. [64], 2021	Contrast Enhanced-Endoscopic Ultrasound	U-Net	Video images obtained from National Taiwan University Hospital, Bei-Hu Branch, and Gifu University Hospital	JI=70%
Li et al. [65], 2020	CT	Position guided deformable UNet (PGD-UNet)	MSD Challenge dataset	DSC for pancreas = 77.01 ± 10.47%, DSC for Tumors = 50.12 ± 30.86%
Alzbeta Tureckova et al. [66], 2020	CT	V-Net	MSD challenge dataset	Dice Score for pancreas= 81. 22% and Dice Score for Tumor= 52.99%
Feng Jiang et al. [67], 2020	CT	DLU-Net	MSD challenge dataset and Changhai Hospital Dataset	MSD Dataset: DLU-Net Accuracy=97.25%, Pr= 88.01%, SI= 94.53%, SP= 97.73%
Ying Liang et al. [68], 2020	MRI	CNN	40 patients with PDAC	DSC=71± 8%, HD=7.3±2.72mm
H. Zheng et al. [70], 2020	MRI/CT	U-NET	1. MRI Dataset from Changai Hospital (20 patients) with PDAC. 2. NIH TCIA pancreas dataset	MRI Dataset:DSC=73.88%, Accuracy=99.86%, Pr=86.06%, Recall=65.42%, NIH CT Dataset:DSC= 84.37%, Accuracy=99.95%, Pr=83.10%, Recall= 86.26%
Zhuotun Zhu et al. [58], 2019	CT	Segmentation-for-classification network	Total 439 CT scans, of which 136 cases having PDAC and 303 cases are normal cases	DSC normal pancreas= 86.9±8.6%, Abnormal pancreas=81.0±10.8%, Tumor=57.3±28.1%, SI=92.7%, SP=99%
Guo et al. [71], 2018	CT	U-Net with LOGISMOS approach	15 patients with pancreatic tumor having 51 arterial phase CT scans	DSC=83.2±7.8%
Yuyin Zhou et al. [72], 2017	CT	Deep FCN	131-CT scans	pancreas DSC=79.23±9.72%, cyst DSC=63.44±27.710%

tumor segmentation is relatively limited. However, until now, no method has obtained satisfactory performance, specifically for tumor segmentation.

Nevertheless, it is worth noting that the segmentation results have exhibited significant improvement over time. This advancement is crucial for future progress in the field. Moving forward, the focus of research will shift towards the development of new or hybrid methods. The pancreas is well known for its significant diversity in form, size, and position while constituting just a tiny proportion of the total

TABLE 4. Research gaps and future directions.

Research Gaps	Future Research Directions
Pancreatic tumor with a size less than 2cm is difficult to segment.	Improved AI based methods will help to precisely segment small size tumors.
The segmentation performance for pancreatic cancer is currently inadequate.	It is crucial to focus on AI based models that can improve the segmentation performance.
Insufficient amount of annotated medical data.	To lessen the dependency on annotated data, alternative learning strategies, including semi-supervised learning and transfer learning, should be investigated.
Complexity of AI algorithms	To improve interpretability and transparency, future research should concentrate on creating AI models that are easy to understand.

CT volume of 0. 5%. As a result, segmenting the pancreatic tumor remains tough. Table 4 represents research gaps and future directions in pancreatic cancer segmentation.

IX. SUMMARY

Automatic segmentation of pancreas and pancreatic tumor is the crucial topic of this in-depth review, which highlights the substantial improvements and difficulties in medical imaging. The review aims to offer a precise overview of segmentation methods and advancements made in the past ten years. A systematic search across various databases and sources is conducted using inclusion and exclusion criteria to perform this detailed review. The segmentation methods for the pancreas are divided into different approaches, including conventional methods that emphasize traditional registration and atlas-based segmentation techniques. Supervised machine learning and deep learning methods focus on CNN, U-Net, and modifications to U-Net architectures. Lastly, unsupervised machine learning concentrates on clustering techniques. Pancreatic tumor segmentation similarly centers around deep learning-based architectures, including variations in the U-Net model. Advancement in deep learning-based methods can overcome the challenges and help to segment the pancreas and tumor segmentation efficiently. The segmentation methods have shown substantial improvement over the years. Though segmentation of pancreatic tumors is quite difficult, the review also highlights the current research gaps that can help researchers focus on developing more effective and accurate segmentation.

X. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In conclusion, the review paper provides a detailed overview and the advancements in pancreas and pancreatic tumor segmentation. Significant progress can be observed in the segmentation of the pancreas and tumor using deep learning methods. Promising results are achieved in the segmentation of the pancreas using deep learning-based methods. The limiting factor is the publicly available labeled datasets which has led researchers to use private datasets for the implementation of pancreatic tumor segmentation. Pancreas segmentation is more extensively explored than pancreatic tumor segmentation due to the different forms and size of tumor. Future research should focus on developing new approaches and enhancing the performance of pancreas and pancreatic tumor segmentation. Standardizing evaluation protocols and utilizing diverse datasets will be crucial in further advancing the field of pancreas and pancreatic tumor segmentation. Additionally, efforts should be made to improve the accessibility of labeled datasets to facilitate research and promote reproducibility. Overall, the advancements made in pancreas and pancreatic tumor segmentation hold great promise for improving diagnosis, treatment planning, and monitoring of pancreatic diseases. Continued research and collaboration in this field will lead to further breakthroughs, ultimately benefiting patients and advancing the medical imaging analysis field.

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