



## **Automated Detection of Pancreatic Tumors via Advanced Image Segmentation**

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### **ABSTRACT**

Pancreatic cancer is one of the leading causes of cancer-related deaths worldwide, largely because it is often diagnosed at an advanced stage and has a poor prognosis. Therefore, detecting pancreatic tumors accurately at an early stage is important for improving treatment effectiveness and increasing patient survival. In recent years, computed tomography (CT) imaging has become an important tool for detecting and evaluating pancreatic abnormalities, as it provides detailed information about the structure and surrounding anatomy of the pancreas. This study proposes an image-processing-based approach for detecting pancreatic tumors from CT images. The proposed method consists of four main stages: pre-processing, segmentation, feature extraction, and classification. In the pre-processing stage, the acquired CT images are enhanced and denoised to reduce unwanted noise and improve their overall quality. The processed images are then segmented to identify the pancreatic region and locate areas that may contain tumors. From these segmented regions, relevant features are extracted to describe the morphological and textural characteristics of the suspected tumor regions. Finally, the extracted features are given to a classification algorithm to differentiate between tumor-affected and normal pancreatic images. Overall, the proposed approach aims to support computer-aided pancreatic tumor detection and contribute to more efficient and accurate early diagnosis.

**KEYWORDS:** Pancreatic tumor, CT images, feature extraction.

## 1. INTRODUCTION

Pancreatic cancer is one of the most serious forms of cancer and continues to be a major cause of cancer-related deaths worldwide. Its high mortality rate is largely associated with the difficulty of detecting the disease at an early stage. Pancreatic ductal adenocarcinoma (PDAC), which is the most common form of pancreatic cancer, can develop rapidly and spread to surrounding tissues and blood vessels. Therefore, early and accurate detection of pancreatic tumors is essential for selecting appropriate treatment strategies and improving patient outcomes.

Computed tomography (CT) is widely used for examining the pancreas because it provides detailed information about the internal structures of the abdomen. However, identifying pancreatic tumors in CT images remains challenging. The size, shape, and position of the pancreas can vary significantly among patients, while tumors may have irregular boundaries and relatively low contrast compared with surrounding soft tissues. Furthermore, the pancreas occupies only a small region of the overall CT image, which makes accurate localization and segmentation more difficult. As a result, manually identifying and measuring pancreatic tumors can be time-consuming and may be influenced by the experience and interpretation of the radiologist.

To overcome these challenges, this study presents an image-processing-based approach for detecting pancreatic tumors in CT images. The proposed system comprises four main stages: preprocessing, segmentation, feature extraction, and classification. During preprocessing, noise in the CT images is reduced and the image quality is enhanced to provide more reliable input for subsequent processing steps. The segmentation stage then focuses on separating the pancreatic region and potential tumor areas from the surrounding tissues. This stage plays an important role in the overall detection process, as the accuracy of segmentation directly influences the quality and reliability of the features extracted in the following stage.

Following segmentation, relevant features are extracted from the identified tumor regions. These features represent important characteristics of the tissue, including intensity, texture, and shape, and help distinguish between normal and abnormal pancreatic regions. The extracted features are subsequently provided to a classification algorithm to determine whether a particular region is likely to contain a tumor. By combining these image-processing steps, the proposed system aims to assist in pancreatic tumor detection while reducing some of the challenges associated with manual analysis of CT images.

The overall objective of the proposed approach is to develop a reliable and efficient computer-aided method for pancreatic tumor detection. By integrating image enhancement, segmentation, feature extraction, and classification, the system is intended to assist radiologists in identifying suspicious regions more effectively and achieving more consistent analysis of pancreatic CT images.

## 2. CONTRIBUTION OF THE PAPER

1. Mainly in explaining why pancreatic cancer develops and which non-genetic factors are associated with increased risk.
2. The study identifies cigarette smoking, chronic diabetes, and obesity as risk factors with very strong evidence. It also reports strong evidence for poor oral health, chronic pancreatitis, heavy alcohol consumption, low intake of fruits and vegetables, and absence of allergy history.
3. It explains that identifying environmental risk factors can help identify individuals at higher risk and support pancreatic cancer screening and early diagnosis.
4. The system focuses on image-based detection, and also focuses on risk assessment and prevention
5. This paper contributes the clinical/risk-factor perspective, while your CT project contributes the image-processing and computer-aided detection perspective. Combining these perspectives can strengthen the motivation for developing systems that support earlier identification of patients or abnormalities.

### 3. RELATED WORK

In [1], the authors proposed an automated three-dimensional (3D) segmentation method for identifying different pancreatic regions in contrast-enhanced CT images. The proposed approach incorporates anatomical information with a naive Bayesian model and integrates these features into a U-Net-based segmentation framework. The model was trained using CT scans of patients with healthy pancreases and evaluated using datasets containing healthy, precancerous, and cancerous pancreatic cases. The reported results demonstrated the potential of the method for supporting early pancreatic cancer detection and treatment planning. However, the authors emphasized that further validation using larger and more diverse datasets is required to establish its reliability and generalizability. The study was supported by the National Institutes of Health (NIH) and was conducted in accordance with relevant ethical requirements. Both publicly available and approved internal datasets were used, with patient-identifying information removed to ensure privacy.

In [3], the authors proposed a convolutional neural network-based approach for the automatic segmentation of pancreatic ductal adenocarcinoma (PDAC) masses and the surrounding abdominal vessels in CT images. The proposed method, referred to as TAU-Net, is a modified version of the Attention U-Net architecture that incorporates dense Scale-Invariant Feature Transform (SIFT) and three-dimensional Local Binary Pattern (3D-LBP) information to improve segmentation. A 3D convolutional neural network (CNN) with 3D-LBP maps was used to localize pancreatic slices, while a hybrid model incorporated information from adjacent slices to improve segmentation accuracy. The reported results demonstrated the potential of the approach for improving PDAC visualization and supporting tumor analysis. The authors also indicated that the method could potentially be extended to

other pancreatic tumors and lesions, with 3D visualization tools providing opportunities for integration into clinical applications.

In [5], the authors investigated the use of convolutional neural networks (CNNs) and other deep learning techniques for pancreatic tumor prediction and classification. The study considered both magnetic resonance imaging (MRI) and CT images and highlighted the ability of CNNs to learn discriminative features directly from medical images, reducing the need for conventional manual feature extraction and, in some approaches, explicit segmentation. A comparative analysis of different machine learning and deep learning techniques was presented, with CNN-based approaches demonstrating strong performance in medical image classification. The study emphasizes the potential of CNNs for automated interpretation of pancreatic imaging data and their broader applicability in computer-aided medical diagnosis.

In [6], the authors discussed the major challenges associated with the early detection, non-invasive classification, and treatment assessment of pancreatic tumors. The study highlighted the importance of advanced medical imaging techniques and image post-processing methods in addressing these challenges. Such techniques can provide detailed information about pancreatic abnormalities and may support the identification and characterization of tumors at an earlier stage. The authors also emphasized that the integration of advanced imaging with improved screening strategies could contribute to better diagnosis and overall management of pancreatic cancer.

In [7], the authors investigated the use of machine learning and image-processing techniques for the detection of pancreatic cancer from CT images. The study addressed the difficulties associated with pancreatic cancer diagnosis and its relatively low survival rate. Several machine learning algorithms, including Particle Swarm Optimization-based Support Vector Machine (PSO-SVM), AdaBoost, and C4.5, were considered for classification. Image-processing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), K-means clustering, and Principal Component Analysis (PCA) were used for image enhancement, segmentation, and feature analysis. The combination of these techniques was intended to improve the extraction of relevant information from CT images and support earlier identification of pancreatic cancer. However, the authors also noted that the high cost associated with advanced imaging and computational technologies may limit their accessibility, particularly in resource-constrained healthcare settings. In [8], the authors investigated the potential of urine-based biomarkers for the early detection of pancreatic ductal adenocarcinoma (PDAC). The study developed a six-protein biomarker panel capable of identifying early-stage pancreatic cancer from urine samples. The findings emphasized the importance of combining multiple biomarkers, including glycoproteins and CA19-9, to improve diagnostic accuracy. The integration of biomarker-based screening with medical imaging techniques was also highlighted as a promising approach for strengthening early PDAC detection and supporting the development of effective screening programs. In [11], the authors investigated pancreatic tumor detection using a minimum distance classifier and

reported an average accuracy of 65.26%. The relatively moderate performance was attributed to the similarity in gray-level intensity between the pancreas and surrounding abdominal organs, which makes tumor identification challenging. To improve detection performance, the study suggested the use of more advanced classification techniques, such as artificial neural networks, support vector machines, genetic algorithms, and fuzzy logic. The authors also indicated that feature extraction methods, including the Gray-Level Co-occurrence Matrix (GLCM) and Principal Component Analysis (PCA), could provide more informative input to the classifiers and potentially improve detection accuracy.

In [18], the authors discussed the challenges involved in segmenting pancreatic tumors and cysts using deep learning techniques. Compared with the segmentation of the pancreas itself, tumor and cyst segmentation is more difficult because of the complex appearance and variability of pancreatic abnormalities. Deep learning methods have therefore gained increasing attention in this area due to their ability to automatically learn complex patterns and discriminative features from large medical imaging datasets. The study provided an overview of the development of different approaches for pancreas and pancreatic tumor segmentation, highlighting the progression from conventional image-processing methods toward deep learning-based techniques.

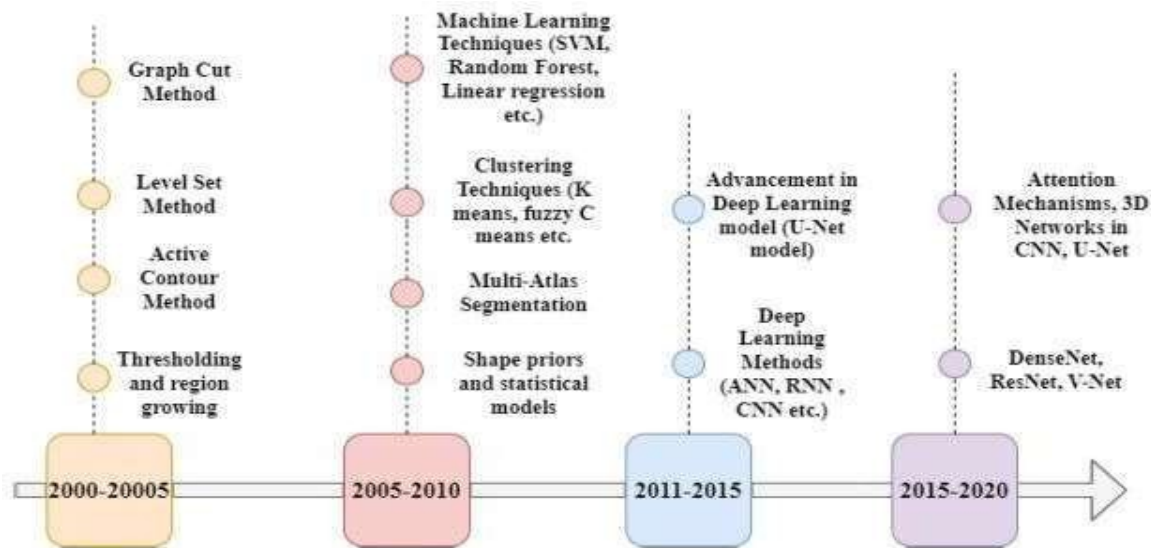


**Figure 1:** Timeline of techniques used for segmenting the pancreas and pancreatic tumors.

#### 4. MATERIALS AND METHODS

In this study, publicly available CT images of pancreatic ductal adenocarcinoma (PDAC) were obtained from The Cancer Imaging Archive (TCIA). The dataset contains a total of 18,255 images distributed across 82 folders. For the initial analysis and experimental evaluation, 50 images were selected as representative samples. The images were provided in DCM format, which is commonly used for storing medical images in the Digital Imaging and Communications in Medicine (DICOM) standard.

DICOM is a widely adopted medical imaging format used for storing, transmitting, viewing, and processing images obtained from modalities such as CT, magnetic resonance imaging (MRI), and ultrasound. In addition to image data, a DICOM file may contain associated patient and examination information, allowing medical images to be linked with their corresponding clinical records. The DICOM standard was developed by the National Electrical Manufacturers Association (NEMA) and has undergone several revisions since its initial development. Its widespread adoption has made it an important standard for the management and exchange of medical imaging data.

The dataset includes three major categories of pancreatic tumors: intraductal papillary mucinous neoplasms (IPMNs), pancreatic neuroendocrine tumors (PNETs), and pancreatic ductal adenocarcinoma (PDAC). The CT images have a resolution of  $512 \times 512$  pixels, with variations in slice dimensions and slice thickness ranging from approximately 1.5 to 2.5 mm. For visualization and examination of the DCM files, GNU Image Manipulation Program (GIMP) software was used on a Microsoft Windows-based system. GIMP is freely available image-processing software that can be used to view and process medical image files after appropriate format support is enabled. The selected CT images provide information that can be used to investigate pancreatic abnormalities and identify imaging characteristics associated with pancreatic tumors. These characteristics form the basis for the subsequent preprocessing, segmentation, feature extraction, and classification stages of the proposed pancreatic tumor detection system.

Two commonly used CT imaging approaches for pancreatic tumor assessment are multiphase CT and cross-sectional CT. Multiphase CT involves acquiring a series of images at different phases following contrast administration, allowing changes in contrast enhancement to be evaluated over time. This approach can provide useful information about the vascularity and characteristics of pancreatic lesions. Cross-sectional CT produces detailed images of the body in multiple anatomical sections, enabling better visualization of the location, size, and extent of a suspected tumor.

Although CT imaging is an important tool for pancreatic tumor assessment, detecting very small tumors can be challenging. In particular, lesions smaller than 2 cm may be difficult to identify because of their small size and limited contrast with surrounding tissues. Therefore, image-processing and computer-aided techniques can be useful for improving the detection and analysis of suspicious regions.

In this study, the Fuzzy Logic Toolbox available in MATLAB (The MathWorks, Inc.) is used to support the development and analysis of the proposed image-processing system. The toolbox provides functions, applications, and Simulink blocks for designing and implementing fuzzy logic-based systems. MATLAB provides several capabilities that are useful for medical image analysis, including visualization and processing of two-dimensional images and three-dimensional image volumes, handling of large and high-resolution datasets, image segmentation, machine learning-based classification, and loading and processing of DICOM images. The use of MATLAB therefore provides

a suitable computational environment for implementing the proposed pancreatic tumor detection system. Its built-in image-processing and machine-learning capabilities can simplify different stages of the analysis, including image enhancement, segmentation, feature extraction, and classification.

**Processed sampled images as follows:**

**Collected Original images:**

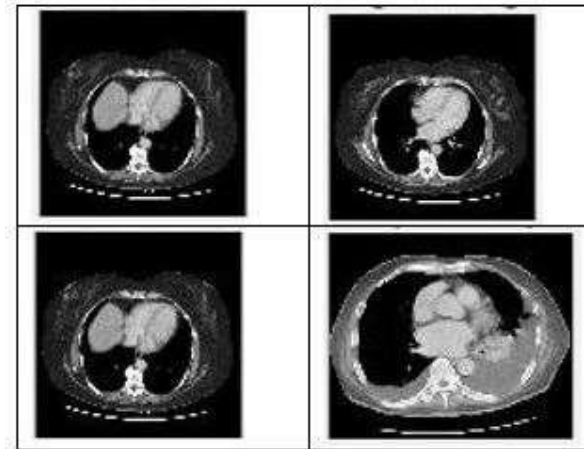


Figure 2 shows collected CT scan images of pancreatic cancer tissues.

Figure 2: CT scan images of pancreatic cancer tissues

**Converted to grayscale image:**

Grayscale conversion is an important preprocessing step in medical image analysis because it simplifies image representation and reduces the computational complexity of subsequent processing. A grayscale image represents intensity information using a single channel rather than multiple color channels, making it easier to process and analyze. This transformation can also improve visualization by emphasizing variations between darker and brighter regions while reducing unnecessary color information.

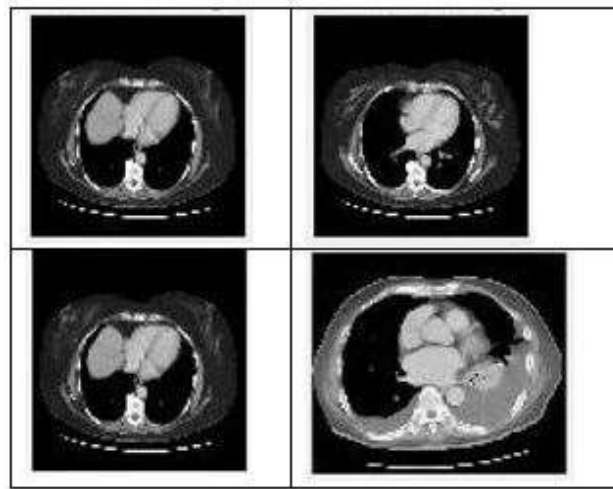
In medical imaging, grayscale representation is particularly useful because modalities such as CT, X-ray, and ultrasound primarily rely on intensity information rather than conventional color information. Different anatomical structures and tissues often exhibit different intensity characteristics, which can be used to distinguish organs, tissues, and abnormal regions. As a result, grayscale images provide a suitable representation for various computer-aided diagnosis and image-processing applications.

Image segmentation is another important stage in medical image analysis. It involves dividing an image into meaningful regions so that different anatomical structures or abnormal areas can be identified separately. In pancreatic CT images, for example, segmentation can be used to distinguish the pancreas from surrounding organs and to isolate regions that may contain tumors. Accurate segmentation allows important characteristics such as shape, intensity, and texture to be analyzed more effectively, thereby supporting subsequent feature extraction and classification.

Both two-dimensional (2D) and three-dimensional (3D) image-processing techniques can be applied to

medical images. In 2D analysis, individual image slices can be processed to highlight regions of clinical interest, while 3D techniques can utilize information across multiple slices to provide a volumetric representation of anatomical structures. Three-dimensional analysis can also support object localization and visualization, whereas 2D detection methods are useful for identifying specific regions of interest within individual CT slices. The selection of 2D or 3D processing depends on the imaging task, available data, and computational requirements.

**Filtered images:**



- Figure 3: Filtered images

The acquired CT images were first converted into grayscale images to simplify the image representation and facilitate subsequent processing. After grayscale conversion, median filtering was applied to reduce noise while preserving important image details and sharp boundaries. The median filter is a nonlinear image-processing technique that is particularly effective for removing impulse noise, commonly referred to as salt-and-pepper noise. Unlike conventional linear filtering methods, median filtering replaces each pixel with the median value of its neighboring pixels, thereby reducing noise while maintaining the edges of anatomical structures. This property makes the median filter suitable for preprocessing medical images, where preserving tissue boundaries is important for accurate segmentation and analysis. The resulting filtered images are shown in Fig. 3.

### Histogram of filtered images:

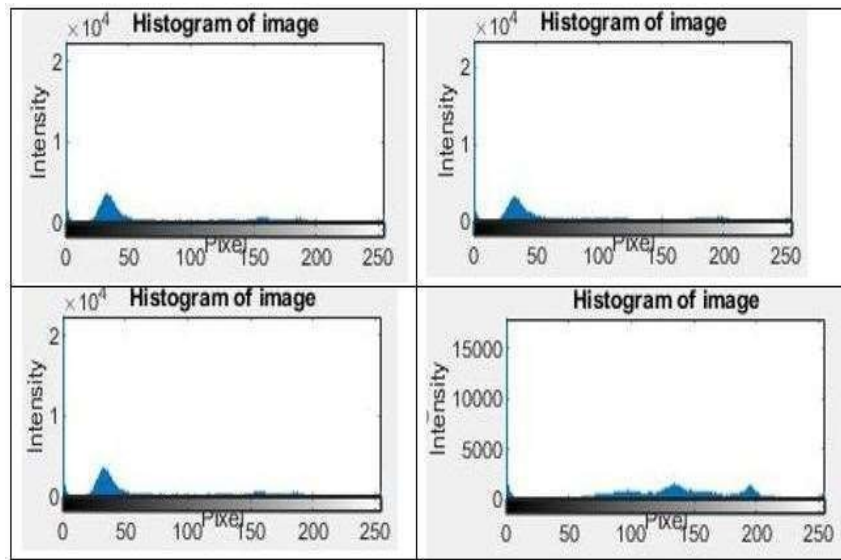


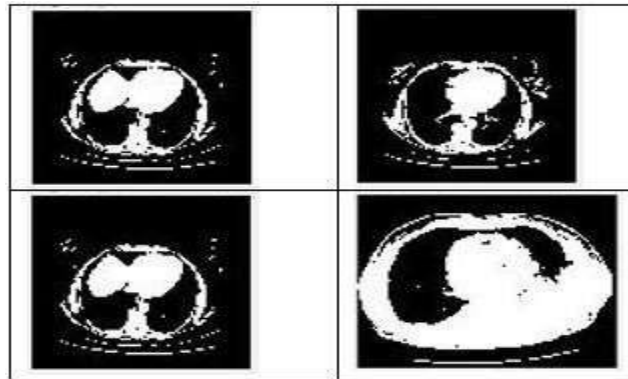
Figure 4: Histogram images

An image histogram is a graphical representation of the distribution of intensity values within a digital image. It indicates the number of pixels associated with each intensity level and provides an overall view of the image's tonal distribution. Histogram analysis can be useful for understanding the brightness and contrast characteristics of an image and for determining whether further enhancement is required during preprocessing. In this study, the histogram of the filtered CT images was analyzed to examine their intensity distribution after noise reduction. The resulting histograms are presented in Fig. 4.

### Converted to Binary images:

Otsu's thresholding method was applied to segment the CT images by separating the pixels into two distinct classes based on their intensity values. Otsu's method is a widely used automatic thresholding technique that determines an optimal threshold value from the grayscale histogram of an image. The selected threshold divides the image into foreground and background regions by maximizing the inter-class variance, or equivalently, minimizing the intra-class variance between the two classes. This enables the relevant regions of the image to be separated from the surrounding background without requiring a manually selected threshold. After applying the calculated threshold, the grayscale images were converted into binary images, where the pixels were represented as foreground and background regions. The resulting binary images are shown in Fig. 5.

Figure 5: Binary images



Found Region of Interest:

Figure 6 shows region of interest derived from binary images.

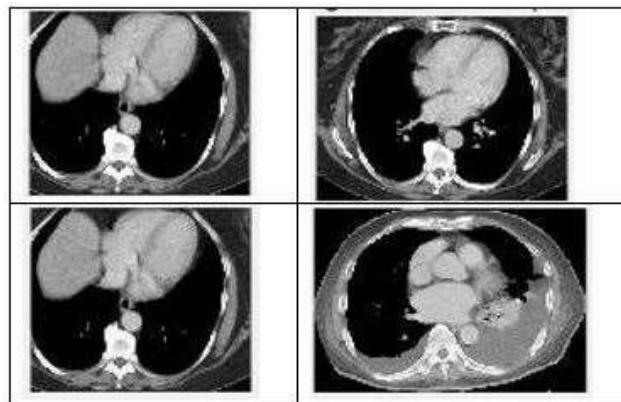


Figure 6: Region of Interest

## 5. CONCLUSION

Pancreatic cancer is one of the most challenging and aggressive diseases, with a relatively low five-year survival rate. Early diagnosis is difficult because pancreatic tumors can be difficult to distinguish from surrounding abdominal tissues in medical images. The increasing availability of diagnostic imaging techniques, particularly computed tomography (CT) and magnetic resonance imaging (MRI), has provided opportunities for detecting pancreatic abnormalities at earlier stages. However, the widespread adoption of advanced imaging technologies can be limited by the high cost of the required equipment and infrastructure, particularly in resource-constrained healthcare settings.

Several image-processing and machine-learning approaches have therefore been investigated for pancreatic tumor detection and classification. One study reported that the similarity in gray-level intensity between the pancreas and surrounding abdominal organs limits the accuracy of conventional detection methods. To address this issue, feature extraction techniques such as the Gray-Level Co-

occurrence Matrix (GLCM) and Principal Component Analysis (PCA) can be used to obtain more informative image features. These features can subsequently be provided as inputs to classification algorithms for distinguishing between different regions of interest within CT images. Machine-learning and deep-learning techniques have also been explored for the classification of pancreatic cancer using both CT and MRI scans.

A typical computer-aided pancreatic tumor detection system involves several processing stages. Initially, CT images are preprocessed to improve their quality and reduce noise that may affect subsequent analysis. Following preprocessing, image segmentation is performed to identify and delineate the pancreatic region and suspected tumor areas. Accurate segmentation is particularly important because it enables the extraction and quantification of local morphological characteristics of the pancreas. These characteristics can provide useful information for tumor analysis and may support early diagnosis and treatment planning.

Although the reported approaches have demonstrated promising results, further validation using larger and more diverse datasets is required to establish their reliability and generalizability. The combination of effective preprocessing, accurate segmentation, informative feature extraction, and suitable classification techniques therefore remains an important area of research for computer-aided pancreatic tumor detection.

Environmental (Non-Genetic, Including Lifestyle, And Clinical Factors) Risk Factors of Pancreatic Cancer by The Level of Evidence,

Table 1: Factors indicating risk level

| Level of Risk | Factors                                                                                                                                                            |
|---------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Very Strong   | Cigarette smoking, chronic diabetes, obesity                                                                                                                       |
| Strong        | Poor oral health/oral hygiene, chronic pancreatitis, no history of allergies, heavy alcohol drinking, dietary patterns with a low amount of vegetables and fruits. |
| Moderate      | Dietary patterns rich in meat and animal products,<br>oral/gut microbiome, hepatitis B or C infection                                                              |
| Unclear       | Environmental tobacco smoke, light to moderate alcohol drinking, physical inactivity, coffee, Helicobacter pylori infection                                        |

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