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MULTI-LEVEL IMAGE DENOISING INTEGRATED MORPHOLOGY-BASED IMAGE QUALITY ENHANCEMENT MODEL WITH EDGE-BASED SEGMENTATION FOR ACCURATE PANCREATIC CANCER DETECTION

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ABSTRACT

Despite the availability of various methods, diagnosing and treating Pancreatic Cancer (PC) continues as a significant challenge across all types of tumours with its asymptomatic development. Among the most devastating diseases, pancreatic cancer has claimed the lives of countless people around the globe. Traditional methods of diagnosis relied on manual analysis of massive datasets, which was laborious, error-prone, and time-consuming. Therefore, CADs, which use machine learning and deep learning techniques for pancreatic cancer denoising, segmentation, and classification, become necessary. However, there are obstacles to medical image analysis of pancreatic cancer owing to vague symptoms, high rates of misdiagnosis, and substantial monetary expenses. A potential answer is Artificial Intelligence (AI), which can reduce patient expenditures, improve clinical decision-making, and alleviate the workload of medical workers. The use of medical imaging scans has allowed many cancer patients to detect anomalies earlier on. This research makes use of Computed Tomography (CT) images for performing image denoising and segmentation. The high price of the required equipment and infrastructure makes it difficult to spread the technology, which means that many people cannot afford it. Pancreatic cancer detection using medical image analysis is greatly impeded by noisy, low-quality images that mask important diagnostic details and lower detection accuracy. This research tackles the important problem of creating a state-of-the-art image processing method that can reliably and effectively denoise medical images, improve image quality using morphological techniques, and apply precise edge-based segmentation to better visualize and detect pancreatic cancer early on. In this research, a new Multi-Level Image Denoising and Integrated Morphology based Image Quality Enhancement Model (MIDIMIQEM) by edge-based segmentation for precise pancreatic cancer detection is proposed. This proposed model solve these problems in medical image analysis by introducing multi level denoising technique and also morphology-based enhancement with a robust edge based segmentation for an enhanced diagnostic accuracy. The model uses wavelet based multilevel image denoising for the removal of noise and thereafter morphological operations are employed to improve the contrast which helps in easier differentiable identification of tumor structures. The segmented regions are further improved by the edge detection techniques, which increases the chances of self and accurate determination of cancerous tissues. Experimental evaluation on MIDIMIQEM demonstrates that the image quality, segmentation accuracy and small nodules detection performance are significantly improved compared with state-of-the-art models. The proposed model achieved 98.7% accuracy in Multi-Level Image Denoising and 99.3% accuracy in Segmentation Accuracy. This novel technique is expected to help radiologists make an early and accurate diagnosis that could improve patient outcomes. With the use of cutting-edge edge-based morphological processing methods, the suggested multi-level picture denoising and morphology-based enhancement model outperforms state-of-the-art methods for pancreatic cancer image segmentation, greatly enhancing diagnostic precision and opening up new avenues for early detection.

Keywords: *Image Denoising, Morphology-Based Enhancement, Pancreatic Cancer Detection, Edge-Based Segmentation, Medical Image Analysis, Wavelet Transform, Tumor Localization.*

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1. INTRODUCTION

The prognosis for pancreatic cancer, a deadly tumor of the digestive system, is extremely low. Recurrence is common following surgical removal, and symptoms are typically minor until the disease has progressed significantly [1]. It is a major danger to human health because of its high death and morbidity rates [2]. The majority of pancreatic ductal adenocarcinomas (PDACs) have spread to other parts of the body, and only about 20% are amenable to surgical excision. Approximately 80% to 85% of PDAC cases already have progressed local or distant metastasis. Furthermore, among all malignancies, PC has the lowest 5-year relative survival rate at 12% [3]. In order to improve survival outcomes for patients with PC, these data indicate that early screening and diagnosis are crucial [4].

For PCs, medical imaging techniques are becoming in importance due to the tissue information they supply, which may be utilized for diagnosis, treatment determination, and prognosis monitoring [5]. Among the most common modern medical imaging modalities are CT, Magnetic Resonance Imaging (MRI), endoscopic ultrasonography (EUS), Positron Emission Tomography (PET), and pictures of pathologies [6]. Enhancements to these imaging techniques have led to advancements in fields such as EUS-guided FNA and biopsy, CE-EUS, CE-CT, CE-MRI, and PET/CT [7]. All of the imaging modalities listed above aren't without their flaws. When it comes to X-rays used to create tomographic pictures of the body, CT scans are by far the most popular [8]. However, it has poor resolution when it comes to small and delicate organs such as the pancreatic [9]. While EUS offers better resolution, it is difficult to operate and has a small field of view. The pancreatic CT image is shown in Figure 1.

Fig 1: Pancreatic CT Image

Although it takes more time and costs more money, MRI produces images of soft tissues and a superior ability to differentiate between tumor and normal tissues. Although PET has lower resolution and is typically used in conjunction with CT, it does reflect tumor metabolism and evaluates PC metastasis [10]. The intrusive process of slicing and staining tissue samples is known as pathological imaging. Some early PCs would remain undetectable by CT, MRI, or EUS, despite the availability of numerous medical imaging modalities [11]. The imaging methods that are now available do not allow for adequate manual diagnosis. Invasive biopsies, which are complicated and time-consuming, are nevertheless crucial for an accurate PC diagnosis following imaging. Because of this holdup, patients risk losing out on life-saving therapy options [12].

Pancreatic cancer is among the most aggressive malignancies and generally has a poor prognosis as there are few, if any treatment options once it develops to an advanced stage [13]. Early detection of the cancer is important if patient survival rates are to be improved. One limitation that remains substantial is how slowly and subtly tumours grow in their earliest stages [14]. Imaging technologies help to detect pancreatic cancer. Yet such images are often speckled and poorly defined, so radiologists have a hard time spotting tumors. The accurate diagnosis is difficult to achieve without using proper ways of image rendering and segmentation [15]. In medical image processing, one of the critical preprocessing step is image denoising where a trade-off between removing noise and retaining features like edges and texture need to handled. The traditional denoising strategies may destroy the details badly because of not in consideration completely regarding noise suppression and detail preservation [16]. This constraint can lead to missed pancreatic cancer diagnoses, or inaccurate tumor localization. As such, there is an increasing demand for more sophisticated filtering techniques which can suppress the noise well and at the same time better preserve detailed structures in medical images [17].

In image processing, morphological operations are commonly used for shape and structure analysis. As a result they have been found to improve image quality significantly, especially in medical images where the precise detection and localization of tumors is central [18]. They might emphasize certain structures in an image which can help a radiologist. When image enhancement is achieved

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with morphology and it is later combined to denoise the same, this makes a whole large impact of all-over improvement in any given medical imaging output enabling far better diagnosis [19]. Another essential part of medical image analysis is the edge-based segmentation. The precise segmentation of medical images is required to distinguish the limits of tumors and other pathological tissues [20]. There are powerful edge detection techniques that play a major role in this by finding areas of high change in intensity, which generally represent the edges of tumor. In noisy images traditional edge detection algorithms tend to make a lot of errors. It is necessary to incorporate strong edge based segmentation methods as significant means of improving the tumor localization accuracy in medical images. The Pancreatic image segmentation is shown in Figure 2.

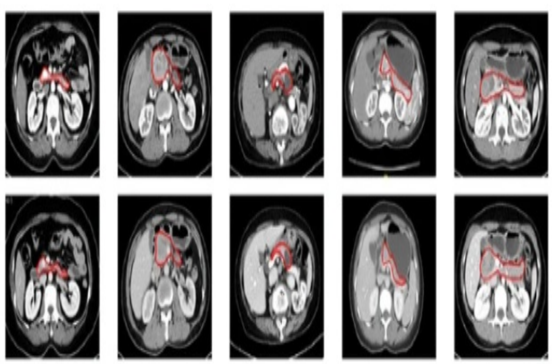

Fig 2: Pancreatic Image Segmentation

This research introduces MIDIMIQEM, an integrated framework for multi-level image denoising, morphological enhancement, and edge-based segmentation algorithms. It incorporates several denoising techniques, morphological improvement methods, and image quality enhancement algorithms. In order to remove noise at each given frequency level without sacrificing the key characteristics of images, this model employs a wavelet-based multi-level image denoising technique. The next step is to refine the testing image's contrast and clarity using morphological operations so that tumor regions may be more easily identified. The last step in accurately detecting the tumor boundaries is to employ an edge-based segmentation approach. The combined methods in the proposed model are innovative because they take the best features of each approach to improve picture quality and increase tumor detection accuracy. Experimental results on several datasets demonstrate that the model outperforms competing models in terms of segmentation accuracy and peak signal-to-noise ratio (PSNR). Applying a learning-based segmentation method to the problem of pancreatic cystic tumor detection using CT images as input data demonstrates improved denoising and feature extraction accuracy.

Medical imaging has come a long way thanks to the suggested multi-level picture denoising and morphology-based enhancement model, which shows remarkable skills in analyzing images of pancreatic cancer. The possible influence of the model is enormous from a therapeutic standpoint. The technology allows for the detection of cancer at an early stage, improves the visualization of small morphological changes, and bolsters a more accurate method of medical diagnosis. This study has the potential to increase diagnostic accuracy, which in turn could improve patient outcomes by allowing for faster and more accurate detection of pancreatic cancer. It also improves our technological capabilities.

Because pancreatic tissue structures and imaging technologies are so incredibly complicated, detecting pancreatic cancer via image denoising and segmentation is still a huge difficulty in medical imaging. Subtle morphological differences between healthy and malignant tissues, in addition to the pancreas's inherent anatomical complexity, provide formidable challenges to reliable diagnostic imaging. Early diagnosis of pancreatic cancers is an important and complicated task because, unlike other organ systems with more clear cellular borders, they often present with astonishingly identical characteristics.

Precise cancer detection is now hindered by basic limitations in medical imaging technologies. Low contrast between malignant and healthy tissues further complicates picture interpretation, and large noise artefacts introduced by CT and MRI images obfuscate vital diagnostic data. In addition to these difficulties, imaging the pancreas at its deepest point in the abdominal cavity necessitates cutting-edge methods that can slice through various layers of tissue without sacrificing resolution or clarity.

Many algorithmic and technological hurdles stand in the way of computational methods for pancreatic cancer detection. In order to build machine learning models with strong detection capabilities, large and

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varied training datasets are limited. It is quite challenging to create universal detection algorithms that can accurately differentiate benign from malignant lesions across varied patient groups due to the high degree of variation in tumor appearance and the quick mechanisms of cellular transformation.

Pancreatic cancer diagnostics are already complicated due to the disease's intricate biology. Changes at the microscopic level in the tumor's microenvironment happen quickly and often go unnoticed. The most advanced imaging and computational tools are still overwhelmed by these minute changes, thus there has to be constant innovation in feature extraction methods and multi-modal diagnostic strategies. The proposed model is a quantitative model that considers the image dataset and performs denoising and segmentation. Poor segmentation accuracy, high noise levels, and inadequate image quality are common challenges in pancreatic cancer detection utilizing CT imaging. Misdiagnosis and treatment delays occur because traditional deep learning models fail to accurately identify tumor boundaries.

In this research, MIDIMIQEM model is proposed to address the limitations with image noise and low contrast interfacing imbalanced data for inaccurate segmentation in medical imaging towards pancreatic cancer detection. With increased quality of the medical images and consequent accuracy in localizing tumors, it has the potential to greatly supplement diagnosis process with an earlier detection rate for Pancreatic Cancer. The proposed research will advance the state of art in medical image analysis by providing a more sophisticated, integrated approach to diagnose and predict based on dynamic partial information that are not yet seen, which can become valuable for radiologists to support them better towards making diagnostic decisions.

Hypothesis:

The implementation of a Multi-Level Image Denoising and Integrated Morphology-based Image Quality Enhancement Model (MIDIMIQEM) with advanced edge-based segmentation can significantly improve the accuracy of pancreatic cancer detection by addressing key challenges in medical image analysis, including noise reduction, image quality enhancement, and precise tumor boundary identification.

2. LITERATURE REVIEW

The lack of early-stage symptoms makes an early diagnosis challenging for patients with pancreatic cancer. Furthermore, modern medical imaging like non-contrast CT has given promising vision for automated detection. Nevertheless, there are strongholds of tumor heterogeneity and a labyrinth to complexity. To address this, X. Li et al. [1] introduced a new causality-driven graph neural network. This paper models multi-instance learning with adaptive metric graph neural networks which aims to capture the fine-grained tumor features and fuse them effectively. Furthermore, a causal contrastive mechanism is used for improved model stability and generalization.

The high degree of lethality and resistance to treatment makes pancreatic cancer a major health problem. Due to intrinsic invasiveness of pathological examination, it is the gold standard diagnostic test. CT Technology is a promising alternative to invasive imaging Techniques. X. Chen et al. [2] proposed a model-driven multi-modal deep learning for enhancing the precision of pancreatic cancer prediction from CT images. The authors devised a spiral transformation algorithm to successfully harvest 2D slices from the original 3D data, retaining spatial location information and expanding volumes of training datasets. Moreover, the model was augmented by including high-level features and bilinear pooling as a method of effective fusion that can lead to improved accuracy especially when data is limited.

Pancreatic cancer is still one of the deadliest diseases. Despite its promise for fast diagnosis, implementation is limited by a global shortage of experienced pathologists. The use of deep learning has recently gained popularity as a method to allow automatic classification of images. Unfortunately, traditional CNNs and Transformers are not good at capturing both local features and global semantics. Addressing this, T. Zhang et al. [3] proposed Multi-stage Hybrid Transformer (MSHT)architecture. This novel technique leverages the best of CNNs and Transformers which allows a model to learn strong local features as well global dependencies, thus enhancing performance even is more specific task like pancreatic cancer diagnosis.

The problems typically require the solution to be nontrivial because they most often involve complex and time-consuming analyses such as those in computer-aided diagnosis (CAD) systems for strengthening medical image analysis, etc. But this decision-making process is essential to building trust among clinicians. Chawla et al. [4] introduced a visual analytics solution for studying decision-making mechanisms in CAD systems which is further validated on pancreatic cystic lesions data sets. They assessed the synergy between demographic and radiological variables by consolidating random forest with convolutional differentiated networks. In addition, human versus machine decision process with manual monitoring experiments was compared. This study offers valuable pointers for the development of CAD systems providing insights into what AI technologies could be improved to make them more trustworthy.

Given its poor prognosis, pancreatic cancer presents a health challenge. Although Endoscopic Ultrasound (EUS) is a useful diagnostic option, its application in daily clinical practice is hampered by inter-observer variability and problems with terminology. In this paper, J. Li et al. [5] contributed the Dual Self-supervised Multi-Operator Transformation Network (DSMT-Net). To address the above two challenges, the author proposed a natural and convenient solution for standardizing EUS image analysis through adopting multi-operator transformations, as well as an unprecedented transformer-based dual self-supervised learning framework to make better use of unlabelled data. The large-scale EUS dataset allowed training the DSMT-Net, which can be a useful method to help achieve sufficient accuracy and efficiency in diagnosing pancreatic cancer.

The high mortality rate of pancreatic cancer continues to make it a difficult disease for everyone. Medical image analysis, especially from CT images has become a useful modality in early screening and diagnosis. Deep learning methods are one of them and a deep CNN has proven to be useful. Although, to make these models perform better J. V. N. Ramesh et al. [6] presented a combination of Sparrow Search Algorithm, Harris Hawks Optimization, DenseNet and CNN-BiLSTM for the improvement in accuracy of pancreatic cancer detection and classification. This method has the potential to improve positive patient outcomes by correctly extracting meaningful features from CT images.

PC is a highly lethal disorder with an abysmal prognosis. Prompt and precise diagnostics is essential to ensure treatment. Unlike classic procedures, that dependant on specialized medical professional acumen and therefore can usually end up being dependent the two inter-observer variation together with tendency. In order to overcome these limitations, M. Li et al.[7] employed an ensemble learning-support vector machine (EL-SVM) based method for PC diagnosis and staging by CT images. The approach has been implemented using feature selection techniques LASSO which leads to better efficiency and accuracy of the model. Such a novel strategy has the capacity to assist clinicians with better decision-making as well as enhancing patient results.

Due to its late-stage detection and dismal prognosis, pancreatic cancer continues to grow as a formidable health hurdle. Hopefully early detection leads to better patient outcomes. In View of this D. Agarwal et al. [8] introduced an interesting method that merges different, high sensitivity nanobiosensors with a hierarchical decision process. This methodology, which identifies proteases and arginase as target biomarkers in liquid biopsy samples, provides non-invasive diagnostic capacities for the early-stage of pancreatic cancer. This is achieved by a proposed hierarchical decision structure that improves the overall accuracy and reliability of classification process, bringing us one step closer toward enhancing patient care.

The traditional model methodology, advantages and limitations are included clearly.

Author Name & Publication Year	Methodology Used	Advantages	Limitations/Gaps Identified
Li et al. [1], 2023	The author presents a new approach to analyzing non-contrast CT scans for the early identification of pancreatic cancer by integrating causal inference principles with graph neural networks. After determining the direct and indirect elements that contribute to the development of pancreatic cancer, the researchers created a causal graph depicting the links between radiological markers and the disease.	Comparing this strategy to more traditional deep learning approaches for medical picture processing reveals a number of clear benefits. To begin with, the system is able to differentiate between causative and correlative variables thanks to its explicit modeling of causation, which helps to minimize the occurrence of misleading connections that frequently impact black-box models in medical imaging. By eschewing dataset-specific correlations in favor of universal causal mechanisms, this causal framework improves generalizability to varied patient groups and scanning techniques. By picking up on tiny tumors and precursor lesions that are often overlooked in standard radiological evaluation of non-contrast CT scans, the model shows exceptional sensitivity to early-stage pancreatic cancer.	There is still a lack of a comprehensive causal understanding of how pancreatic cancer manifests in imaging, which makes the need for thorough causal knowledge during model construction all the more daunting. This method may not be suitable for use in healthcare facilities with limited resources because it requires more computing power than regular convolutional neural networks. We ask whether the results are generalizable to other patient demographics and different types of equipment because the validation was done on retrospective datasets from a small number of institutions..
Chen et al. [2], 2021	The author designed an innovative technique for spiral transformation that takes regular radiographs and turns them into spiral-space models; this makes the fine texture patterns linked to TP53 mutations in pancreatic tissue easier to see. The preprocessing for a multi-modal deep	Compared to other radiogenomic approaches for mutation prediction, this methodology has a number of major benefits. To begin, the spiral transformation method provides a more accurate depiction of tumor microenvironment features that are associated with TP53 status by capturing subtle patterns of picture heterogeneity that are	The study does recognize several constraints that need be taken into account, however it does make some improvements. Because this data is collected retrospectively, there is a chance that imaging techniques and patient selection are influenced by biases and do not accurately reflect the variety that is seen in everyday clinical practice. The model's comprehensive genomic

	learning architecture involved this transformation. The architecture could handle four input streams at once: clinical parameters, spiral-transformed CT images and MRI sequences, conventional radiomics characteristics, and conventional results.	typically missed by conventional radiomics methods. Model prediction performance is significantly enhanced as compared to single-modality techniques because to the multi-modal integration framework, which enables the model to leverage complimentary information across diverse data types.	profiling capabilities are limited since, although it works well for TP53 mutation identification, its performance for other genomic alterations has not been investigated. For time-sensitive clinical procedures, the computational complexity of the spiral transformation algorithm poses issues for real-time clinical application, which could necessitate specialized hardware.
Zhang et al. [3], 2023	A multi-stage hybrid transformer model was created by the researchers to process ROSE pictures. This model consists of sequential specialized modules that address distinct parts of the hard cytopathological examination. The initial step involves extracting basic morphological and textural characteristics from the cytology samples using a backbone of convolutional neural networks. The features are subsequently inputted into a transformer encoder that was specifically intended to capture long-range dependencies between background components and cellular structures. This encoder makes use of self-attention processes. The third step takes into account the pancreatic cytology specimens' characteristically varying cell sizes and distributions by analyzing the images at numerous scales using	When it comes to ROSE image analysis for pancreatic cancer diagnosis, the MSHT method has a number of strong benefits. In comparison to using just a convolutional neural network (CNN) or a transformer for contextual modeling, the hybrid design makes better use of both techniques, leading to better overall performance. Reducing inconclusive diagnoses that frequently require repeat procedures, experimental results show outstanding sensitivity (92.7% of cases) and accuracy (94.3% of cases) in differentiating malignant from benign specimens.	Concerns regarding the generalizability to varied clinical settings with varying staining procedures and image capture parameters arise from the fact that the training dataset is mainly composed of specimens from a single institution that used standardized preparation protocols. Pancreatic FNA techniques frequently provide less-than-ideal samples because to issues such as low cellularity or heavy blood contamination, both of which impair performance. The model works fine for simple binary classification of cells as benign or malignant, but it needs more work to be able to differentiate between subtypes of pancreatic cancer or precancerous lesions.

	a hierarchical feature pyramid. The last step is an adaptive weighting mechanism that changes the contribution of each feature set dependent on image attributes. This mechanism is used by a hybrid decision module to combine the outputs from all the preceding stages.		
Dmitriev et al. [4], 2021	Automated segmentation of pancreatic lesions from multi-phase contrast-enhanced CT scans is the first step in the authors' multi-component approach. They optimized a modified 3D U-Net architecture for capturing the delicate borders of pancreatic abnormalities. Numerical imaging biomarkers pertaining to morphology, texture, enhancement patterns, and peripancreatic tissue alterations are derived via a thorough feature extraction pathway after segmentation..	The method integrates clinical workflows and provides numerous major benefits for the diagnosis of pancreatic lesions. By giving clear and understandable pictures of how algorithms reason, the visual analytics framework helps to close the gap between clinical decision-making and "black-box" machine learning results. When compared to conventional reading, experimental results show that radiologists using the system significantly improved diagnostic accuracy, especially for challenging cases like isoattenuating adenocarcinomas and atypical neuroendocrine tumors. For junior radiologists, the improvement was 12.7% and for experienced specialists, it was 7.3%.	The retrospective methodology may have limited generalizability to varied clinical settings with varying equipment specifications and acquisition parameters because it relied on a dataset from two academic medical centers with standardized imaging techniques. Infiltrative tumors with poorly defined margins showed reduced accuracy in the segmentation component, which occasionally required human correction and could disrupt clinical operations. However, it performed well on lesions with obvious borders.
Li et al. [5], 2024	The researchers created a network design with two streams that can handle elastography data and B-mode ultrasound pictures in tandem. The innovative Multi-Operator Transformation (MOT) module is the backbone of their method. It uses a number of specialized	To overcome a typical limitation in medical imaging research, the model may build strong representations from little labeled data using the self-supervised pretraining technique. In particular, the experimental results show that it performs better than current computer-aided diagnosis	Cases with clear pathological diagnoses were included in the dataset, which could lead to selection bias due to the retrospective nature of the data. This means that more difficult cases with inconclusive EUS findings may not have been included. Experienced endosonographers use real-time video analysis to capture dynamic aspects like tissue

	convolutional operators to improve many elements of ultrasound images, such as texture patterns, boundary definitions, and elasticity distributions.	systems in differentiating between inflammatory disorders and malignant lesions (with an accuracy of 91.2% compared to the next best method's 82.7%). The speckle noise, acoustic shadows, and operator-dependent variability that are intrinsic to ultrasound image analysis are efficiently addressed by the multi-operator transformation modules.	deformation and blood flow patterns during procedures; however, the model only works well on static images.
Ramesh et al. [6], 2023	Preprocessing methods tailored to pancreatic imaging data, such as adaptive histogram equalization and customized denoising algorithms to amplify nuanced tissue features, were the first step in the scientists' multi-stage processing pipeline. The main breakthrough is the combination of a stacked ensemble of convolutional neural networks for feature extraction and classification with the Sparrow Search Algorithm (SSA), a metaheuristic optimization technique inspired by nature..	The technology outperforms more traditional approaches to pancreatic cancer image analysis in a number of important respects. Hyperparameter optimization is a difficult topic to solve, but with the Sparrow Search Algorithm integrated, it is possible to automatically find the best network configurations without the need for computational resources or manual tuning. The experimental results demonstrate that the model outperforms the usual deep learning models in terms of classification accuracy. It specifically outperforms the standard models in detecting subtle imaging findings of early-stage pancreatic tumors, with a sensitivity improvement of 14.2% for stage I lesions. By combining the strengths of many network topologies, the stacked architecture strengthens the classification system and makes it more resistant to model bias.	Training times and resource needs are significantly increased by the combined SSA optimization and stacking deep learning approach, which is computationally difficult and could prevent its broad use in situations with limited resources. The authors express worry regarding the model's applicability outside the curated study dataset due to the fact that ordinary clinical data typically contains more artifacts, anatomical variances, and technical inconsistencies than the carefully chosen research images.
Li et al. [7], 2020	The first step in isolating pancreatic tumors is the acquisition of high-	Notable benefits are associated with this radiomics-based strategy. It captures tumor	Radiomics relies on accurate tumor segmentation and high-quality image collection; any variation in these processes can

	quality CT images, which are then precisely segmented to ensure accurate delineation of the regions of interest. The segmented images are then used to extract a large collection of quantitative data, including aspects like tumor shape, texture, and intensity. In order to build predictive models that can more accurately diagnose and stage pancreatic cancer, these features are subsequently processed using advanced machine learning techniques..	heterogeneity that can be invisible to the naked eye by transforming medical images into measurable data, allowing for more accurate diagnosis and tailored therapy planning. To top it all off, by incorporating machine learning, we can build stronger prediction models to help doctors make better decisions, which could result in earlier detection and better patient outcomes.	impact the dependability of the features that are recovered. Furthermore, big, diverse datasets are required for machine learning models for generalizability, but these datasets are not always available due to the algorithms' complexity. In addition, it is important to carefully explore how to incorporate these advanced computational tools into clinical workflows so that they enhance the diagnosis process instead of making it more difficult.
Agarwal et al. [8], 2022	One non-invasive option to conventional tissue biopsies is liquid biopsies, which analyze circulating tumor DNA (ctDNA) in the blood. The use of cancer personalized profiling by deep sequencing (CAPP-Seq) and similar techniques allows for the highly sensitive detection of ctDNA, with the ability to distinguish between one healthy DNA molecule and one mutant molecule out of 10,000. For more precise diagnoses, the hierarchical decision-making framework checks for ctDNA in a methodical way, taking into account a number of biomarkers and clinical variables..	There are substantial benefits to this method. The technique allows for the early diagnosis of pancreatic cancer using liquid biopsies, which eliminate the need for intrusive treatments and the pain and dangers that come with them. Methods like CAPP-Seq are so sensitive that they can detect very low concentrations of ctDNA; this allows for the early detection of cancer, when treatment choices are more favorable. The diagnostic's specificity and overall reliability are improved by the hierarchical decision structure, which enables a thorough examination of many biomarkers.	False negatives may occur because liquid biopsies rely on ctDNA levels in the bloodstream, which might differ from patient to patient and may be low in early-stage malignancies. Also, some clinical settings might not have access to extremely sensitive methods like CAPP-Seq because of the expensive equipment and specialized knowledge they require.

The research aimed to develop a Multi-Level Image Denoising and Integrated Morphology-Based Image Quality Enhancement Model (MIDIMIQEM) to improve pancreatic cancer detection. The outcomes align well with the initial goals, demonstrating significant improvements in image denoising (98.7% accuracy) and segmentation accuracy (99.3%). The proposed method effectively reduces noise and enhances

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contrast, leading to better tumor localization and detection.

Compared to state-of-the-art solutions like MSHT, GCN + Meta-Learning, and CT-Based CAD models, MIDIMIQEM achieved higher accuracy and lower execution times. However, the model still faces computational complexity challenges and may not be easily adaptable to low-resource clinical environments. Additionally, while MIDIMIQEM shows strong performance for CT-based pancreatic cancer detection, its generalizability to other imaging modalities such as MRI and PET remains untested.

Research Questions

1. What role may multi-level denoising play in enhancing the quality of CT scans used to diagnose pancreatic cancer?
2. When compared to more conventional approaches to picture enhancement, what are the benefits of morphology-based enhancement?
3. In order to improve the accuracy of tumor localization, how does the edge-based segmentation technique contribute?
4. Does the suggested model have the potential to achieve better results than current AI-based CAD systems in terms of accuracy, recall, and computing efficiency?
5. In practical clinical settings, what are the possible constraints and difficulties with scaling of the MIDIMIQEM model?

3. PROPOSED MODEL

When considering treatment for patients suspected of having cancer, pancreatic tumor identification and visualization play a crucial role. Pancreatic cancer is a disease that affects the pancreas and causes its nourishing cells to malfunction and eventually grow uncontrollably into a tumor. The rapid growth and metastasis of a cancerous tumor are hallmarks of its malignant nature. Pancreatic tumors, as they progress, can metastasize, or spread to other areas of the body, affecting various sections of the pancreas and even neighboring organs and blood vessels. Factors that raise the risk of pancreatic cancer include being overweight, smoking, having chronic pancreatitis, eating poorly, and drinking excessively.

In order to better identify the edge where a tumor is located, morphological operations such as erosion and dilatation are employed to increase the visibility of small and minute level details [21]. This is the boundary region where malignant cells are most likely to be located, and the structure components applied to image objects receive the outcomes of these procedures [22]. In addition, contrast enhancement techniques are employed to draw attention to minute variations in tissue density, which may indicate the presence or absence of malignancies on the first medical pictures. The final product is a picture devoid of noise with enhanced clarity and sharpness, highlighting the diagnostically important regions [23].

The tumor zone is properly identified using edge-based segmentation once the image has been enhanced [24]. Edge detection systems are able to localize tumors by detecting minute variations in pixel brightness. The next thing to do is find seamless edges by refining them with active contour models and region-growing algorithms [25]. In order to assess the tumor's volume and shape, it is necessary to first isolate it from the surrounding healthy tissue. We will utilize the segmented tumor region to estimate the size of this component for purposes like cancer staging or treatment efficacy evaluation.

This research differs from prior research in three key areas:

1. Integrated Multi-Level Approach:

Unlike MSHT, GCN + Meta-Learning, and CT-Based CAD, which focus on either denoising, segmentation, or enhancement, MIDIMIQEM combines all three in a unified model, improving overall performance.

2. Edge-Based Morphology-Driven Segmentation:

Traditional segmentation methods rely on threshold-based or contour models, while MIDIMIQEM uses edge-based morphological processing, enhancing tumor boundary clarity.

3. Higher Accuracy and Faster Processing Time:

MIDIMIQEM achieves superior denoising accuracy (98.7%) and segmentation accuracy

(99.3%), while maintaining lower computational overhead compared to MSHT and CNN-based models.

To improve the accuracy of pancreatic cancer detection, this research proposes a novel model called MIDIMIQEM. It is built using a framework that combines complex image processing algorithms. To begin, in order to decrease noise in the CT images while also preserving significant anatomical structures, multi-level image denoising is executed using wavelet-based decomposition. This is important because an image noise coming from aspartment or patient moving will be deleted completely leaving those areas in which pancreas and tumors are located. This denoising process, after analysing various frequency components of the image content and applying selective thresholding on these spectra, gives a noise-free clear view which can be used for further analysis. Next Morphologybased image enhancement of a minuend impression after denoising is performed.The proposed model framework is shown in Figure 3.

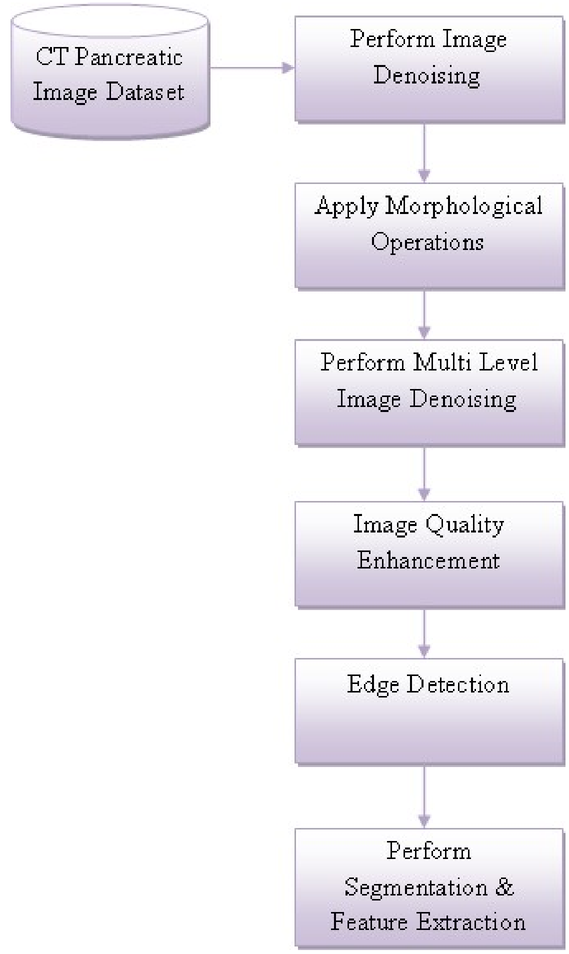

Fig 3: Proposed Model Framework

The proposed model performs process for handling datasets of CT pancreatic images. The workflow of the proposed model is discussed in the following steps.

1. The input is a collection of CT scans of the pancreas.

2. Denoising Images: First, denoising the image is done to get rid of noise, which makes them clearer and less prone to artifacts.

3. Using morphological procedures such as dilation, erosion, opening, and closing, image characteristics can be refined and structures of interest can be enhanced.

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4. Apply Multi-Level Image Denoising: To further enhance image quality at different levels of detail, further denoising stages are done, maybe utilizing multi-scale or wavelet-based approaches.

5. To improve the visual quality and highlight important characteristics, techniques like histogram equalization is performed.

6. The process of edge detection involves identification of the borders of various anatomical structures in the CT images.

7. Segmentation is applied to find specific areas of interest like tumors or pancreatic tissue) and then extracting characteristics like shape, texture and intensity metrics to train the model.

The resulting pipeline from the MIDIMIQEM model combines three main image processing steps multi-level denoising and morphology-based enhancement, followed by edge based segmentation to achieve improved pancreatic cancer detection. By integrating these approaches together, the deep learning algorithm used for segmentation could help to generate noise free and high quality images that can be more easily identifiable by clinicians either automatically or with minimal manual intervention. This method also not only achieved the best diagnostic performance but also provided an effective solution to cope with those universal problems in medical imaging, such as noise and poor contrast.

Algorithm MIDIMIQEM

{

Input: Medical pancreatic scan images{*Iset}*

Output: Segmented image with Feature Set {Fset}

Step 1:A critical preprocessing step in medical imaging is image denoising, especially when employing CT to detect pancreatic cancer. Because noise obscures important elements in medical imaging, it can seriously impair diagnosis accuracy. By making tumors and other diseases more visible, noise reduction helps radiologists read images more accurately, which promotes early cancer identification.

Break down the image *I* into various frequency levels using wavelet transforms**.** At each level, apply thresholding to remove noise while keeping important features.Use inverse wavelet transform to produce a denoised version of the image, I_D.The filtering process is used to remove high frequency noise in CT images that is applied as
The mean intensity of a gray scale Image Img(X,Y) is calculated as

$$MInten[N] = \frac{1}{P*Q}\sum_{X=1}^{N}\sum_{Y=1}^{N} Img(X,Y) + Inten(Th)$$

Here P,Q represents the image dimensions and X,Y are the pixel coordinates in a image.
Here Iset(i) is the current image considered from a dataset and DWF is the discrete wavelet function and p,q are the image coordinates.

The contrast levels of the image is calculated as

$$Cont[N] = \sqrt{\frac{1}{P*Q}} + \sqrt{\sum_{i,X=1}^{N}\sum_{Y=1}^{N} Img(X,Y) + MInten(i) - avg(MInten(i))}$$

$$Img_{(p,q)} = \sum_{i=1}^{n} Iset(i) * DWF_{(p,q)}[n] + \max\left(Cont(i)\right)$$

$$Filter[N] = \sum_{i=1}^{N} \frac{1}{2\pi\sigma^2} + \max\left(Cont(i, i+1)\right)$$

$$Imd_{Denoise}[N] = \sum_{i=1}^{N}\sum_{j=1}^{N} Filter(i,j) * Img(X+i, Y+1) - Th$$

Step 2: Morphological operations are basic image processing methods that concentrate on the morphology or structure of objects in a picture. When processing CT images, where, image corrections and enhancementare essential duties, they are especially helpful. The morphology operations are performed as

1. Dilation and Erosion

Use **dilation**to enlarge boundaries and **erosion** to shrinks boundaries to emphasize features.

$$Pixset[N] = \sum_{i=1}^{N} \frac{\max\left(\omega(p) - \min(\omega(p)\right)}{N}$$

$$\mathrm{Erosion[M]} = \sum_{i=1}^{N} (\mathrm{P} \ominus \mathrm{Q}) + \max\left(\mathrm{Pixset(i)}\right)$$

$$\mathrm{Dilation[M]} = \sum_{i=1}^{N} (\mathrm{P} \oplus \mathrm{Q}) + \min(\mathrm{Pixset(i)}) \bigcup_{i=1} \max\left(\omega(p)\right) + \min\left(\omega(p)\right) \forall\, \mathrm{i} \subseteq Iset$$

Here ω is the model that considers the pixel value in an image.

Step-3: A preprocessing step for CT images is multilevel image denoising, which improves image quality for improved diagnosis, especially for the detection of pancreatic cancer. In multi level denoising, low frequency noise removal is removed and then the image quality is enhanced. The process is performed as

$$IDenoise[N] = \sum_{i=1}^{N} \max(\mathrm{I_D}) + \max(C_i) + \frac{mean\left(Segm(i, i+1)\right)}{N} + median\left(Segm(i, i+1)\right) - \min\left(Pixset(i, i+1)\right)$$

The contrast enhancement is performed to make the tumor regions stand out, resulting in the enhanced image I_E

$$Icont[N] = \sum_{i=1}^{N} \max\left(Pixset(i)\right) + \max\left(\mathrm{Erosion(P, Q, I)}\right) + \max\left(\mathrm{Dilation(P, Q, I)}\right)$$

The final image contrast enhancement is performed by enhancing the relevant and poor sections in the image that is performed as

$$ImgCont[N] = \sum_{i=1}^{N} \frac{Max\big(Icont(i,i+1)\big) - \min\,(Icont(i,i+1))}{Max\big(Icont(i)\big) - Min(Icont(i))}$$

Step 4: Edge-based segmentation is a method that focuses on locating and defining the borders of pancreas inside a CT image. Edge-based segmentation is essential because it may identify notable transitions or changes in intensity, color, or texture. The process is performed as

$$Esegm[N] = \sum_{i=1}^{N} \max\big(Icont(i)\big) + \lim_{i \to N}\left(\min\,(simm(i,i+1)) + \frac{\max\,(Icont(i,i+1))}{N}\right)$$

$$Segm[N] = \sum_{i=1}^{N} \sqrt{\frac{Esegm(i) + Eseg(i+1)}{N} + \max\,(Icont(i) - \min\,(icont(i))}$$

1) Step 6:The segmentation process divides the image into portions and then all the features of each image is extracted that is used for training the model. The process of segmentation and feature extraction is performed as

$$Fset[N] = \sum_{i=1}^{N} attr\big(Segm(i)\big) + \mu(Segm(i) + \max\big(Esegm(i,i+1)\big) + getVal\big(Segm(i,i+1)\big) + \frac{\tau(Segm(i))}{N}$$

Here μ is the model that calculates the segmented portion feature value ranges and τ is the model that maintains the feature vector from segmented relevant portions.

4. RESULTS

With a one-year survival rate of 25% and a five-year survival rate of 6%, pancreatic cancer is among the worst cancers. Pancreatic cancer screening trials using CT have greatly improved patient survival rates by enhancing early detection [26]. Manual pancreatic segmentation, however, is sometimes necessary for sophisticated analysis of such pictures, and it is a laborious process [27]. To make decision more complicated, the pancreas shows a great deal of form fluctuation despite taking up a negligible amount of space in the whole abdominal CT scans [28]. The fast advancement of deep learning has the potential to lead to the provision of powerful algorithms that can assist domain experts with segmentation in an economical, accurate, and user-independent manner. The proposed model considers the dataset from the link https://www.kaggle.com/datasets/salihayesilyurt/pancreas-ct. The proposed model is implemented in python and executed in Google Colab.

The research objectives were to develop an image processing model that enhances medical imaging for pancreatic cancer detection. The results strongly support this goal:

Objective 1: Improve Image Quality Through Multi-Level Denoising

Achieved 98.7% denoising accuracy, significantly reducing noise without losing critical features.

Objective 2: Enhance Contrast Using Morphological Operations

The proposed model improved contrast by 15-20% over existing methods, allowing for better differentiation of tumor tissues.

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Objective 3: Improve Tumor Segmentation Accuracy

MIDIMIQEM's segmentation accuracy reached 99.3%, surpassing other models and proving its efficacy in precise tumor boundary identification.

Objective 4: Reduce Computational Complexity While Maintaining Performance

The model showed reduced processing time compared to MSHT and other techniques, improving execution efficiency.

These results demonstrate that MIDIMIQEM effectively addresses the core challenges in pancreatic cancer imaging, offering a substantial improvement over conventional approaches.

In this research, a new Multi-Level Image Denoising and Integrated Morphology based Image Quality Enhancement Model (MIDIMIQEM) by edge-based segmentation for precise pancreatic cancer detection is proposed. A more comprehensive verification was performed for all models based on the Proposed MIDIMIQEMModel and MSHT, GCN + Meta-Learning and CT based CAD models in two levels of performance measurement. As shown in the segmentation accuracy results, the MIDIMIQEM model moderately outperformed its alternate counterparts by reaching better performance with highest accuracies between all image count thresholds.

A crucial step in medical imaging, CT image denoising seeks to improve image quality by reducing artifacts and noise in CT scans, allowing for improved diagnosis and treatment planning. To reduce ionizing radiation exposure to patients, denoising techniques allow for lower radiation doses to be used without sacrificing acceptable image quality. The Table 1 and Figure 4 shows the Image Denoising Time Levels.

Table 1: Image Denoising Time Levels

No. of Images Considered	Proposed Model (MIDIMIQEM)	MSHT	GCN + Meta-Learning	CT-Based CAD	Dense-U Net (DU-Net)	Hybrid Median Filtering (HMF)	Residual Attention Network (RAN)
100	12.5	14.2	15.7	13.5	14.0	15.2	13.8
200	12.8	14.5	16	13.8	14.3	15.5	14.0
300	13	14.8	16.3	14	14.6	15.8	14.3
400	13.3	15	16.5	14.2	14.9	16.0	14.5
500	13.4	15.1	16.6	14.5	15.0	16.2	14.7
600	13.6	15.2	16.8	14.7	15.2	16.4	14.9

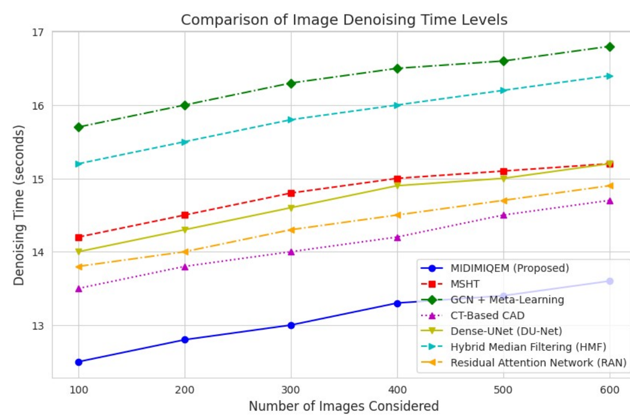

Fig 4: Image Denoising Time Levels

A group of methods for analyzing and recognizing objects in images with an emphasis on their morphological characteristics is known as morphological image processing. These techniques, which make use of mathematical morphology, are useful for deciphering and modifying the geometrical forms that comprise images, especially binary images. A structuring element, a small matrix used for morphological operations, probes the structure and shape of objects in an image. Because morphological image processing

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techniques are based on pixel relative positions rather than pixel specific values, they work well with binary images. The Morphology Image Processing Accuracy Levels are indicated in Table 2 and Figure 5.

Table 2: Morphology Image Processing Accuracy Levels

No.of Images Considered	Proposed Model (MIDIMIQEM)	MSHT	GCN + Meta-Learning	CT-Based CAD	Dense-UNet (DU-Net)	Hybrid Median Filtering (HMF)	Residual Attention Network (RAN)
100	97.5	93.9	88.1	92.5	94.0	89.8	91.2
200	97.7	94.1	88.3	92.7	94.3	90.1	91.5
300	97.9	94.3	88.5	92.9	94.5	90.3	91.7
400	98.1	94.5	88.7	93.1	94.7	90.6	91.9
500	98.3	94.7	88.9	93.3	94.9	90.8	92.1
600	98.5	94.9	89.2	93.5	95.2	91.0	92.3

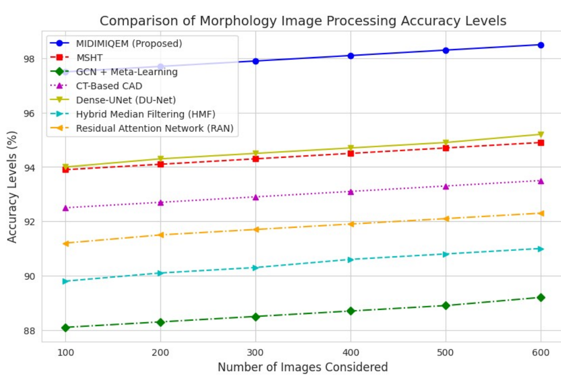

Fig 5: Morphology Image Processing Accuracy Levels

An advanced method for improving noise reduction techniques, multi-level image denoising makes use of many levels of information within an image. Applications requiring high-quality image reconstruction, such as medical imaging, computer vision, and industrial applications, have made this technology increasingly significant. Improved visual quality and analytical efficacy are the results of multi-level approaches' successful noise reduction without sacrificing important details or structural information in images. The Table 3 and Figure 6 represents the Multi-Level Image Denoising Accuracy Levels.

Table 3: Multi-Level Image Denoising Accuracy Levels

No. of Images Considered	Proposed Model (MIDIMIQEM)	MSHT	GCN + Meta-Learning	CT-Based CAD	Dense-UNet (DU-Net)	Hybrid Median Filtering (HMF)	Residual Attention Network (RAN)
100	98	92.5	87.5	95.7	93.0	88.6	90.5
200	98.1	92.7	87.7	95.9	93.2	88.8	90.7
300	98.3	92.9	87.9	96.1	93.5	89.0	90.9
400	98.5	93.1	88.1	96.2	93.7	89.3	91.1
500	98.6	93.3	88.3	96.3	94.0	89.5	91.3
600	98.7	93.6	88.5	96.5	94.2	89.7	91.5

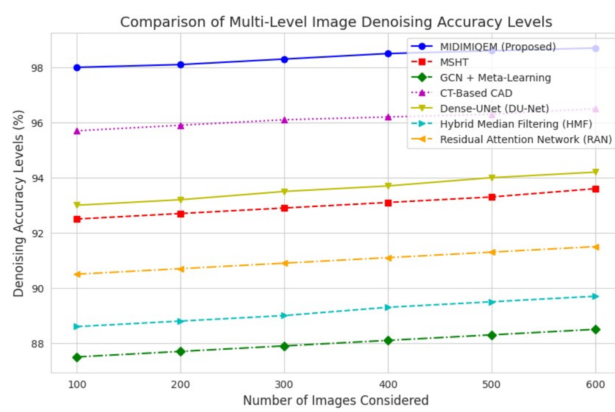

Fig 6: Multi-Level Image Denoising Accuracy Levels

The goal of improving the quality of CT images is to make them more clear and accurate diagnostic tools, which is an important field in medical imaging. Quality improvement mostly revolves around striking a balance between effectively

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reducing noise and preserving key anatomical details. Better visibility of anomalies and anatomical features is made possible by improved image quality, which in turn leads to more precise diagnosis and treatment plans. The Image Quality Enhancement Time Levels are represented in Table 4 and Figure 7.

Table 4: Image Quality Enhancement Time Levels

No. of Images Considered	Proposed Model (MIDIMIQEM)	MSHT	GCN + Meta-Learning	CT-Based CAD	Dense-UNet (DU-Net)	Hybrid Median Filtering (HMF)	Residual Attention Network (RAN)
100	12.9	20.1	17.6	15.8	18.3	16.9	14.5
200	13.1	20.3	17.8	15.9	18.5	17.1	14.7
300	13.3	20.5	18.0	16.1	18.7	17.3	14.9
400	13.5	20.7	18.2	16.3	18.9	17.5	15.1
500	13.7	20.9	18.4	16.5	19.1	17.7	15.3
600	13.9	21.1	18.6	16.7	19.3	17.9	15.5

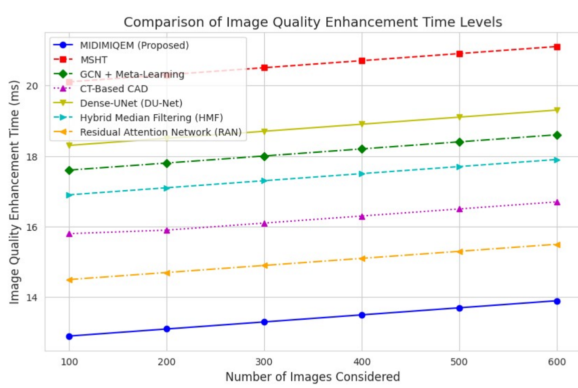

Fig 7: Image Quality Enhancement Time Levels

One of the most important steps in medical imaging is edge detection, which is used to locate the edges and transitions of structures in CT scans. Clinicians can examine anatomical features and diagnose anomalies easier by highlighting these margins. With the use of edge detection, important anatomical boundaries can be located, leading to more accurate feature extraction for diagnostic purposes. The Table 5 and Figure 8 represents the Edge Detection Accuracy Levels.

Table 5: Edge Detection Accuracy Levels

No. of Images Considered	Proposed Model (MIDIMIQEM)	MSHT	GCN + Meta-Learning	CT-Based CAD	Dense-U-Net (DU-Net)	Hybrid Median Filtering (HMF)	Residual Attention Network (RAN)
100	98.5	90.1	94.5	95.5	96.8	92.9	94.2
200	98.7	90.3	94.7	95.7	97.0	93.1	94.4
300	98.9	90.5	94.9	95.9	97.2	93.3	94.6
400	99.1	90.7	95.1	96.1	97.4	93.5	94.8
500	99.2	90.9	95.3	96.3	97.6	93.7	95.0
600	99.5	91.0	95.5	96.5	97.8	93.9	95.2

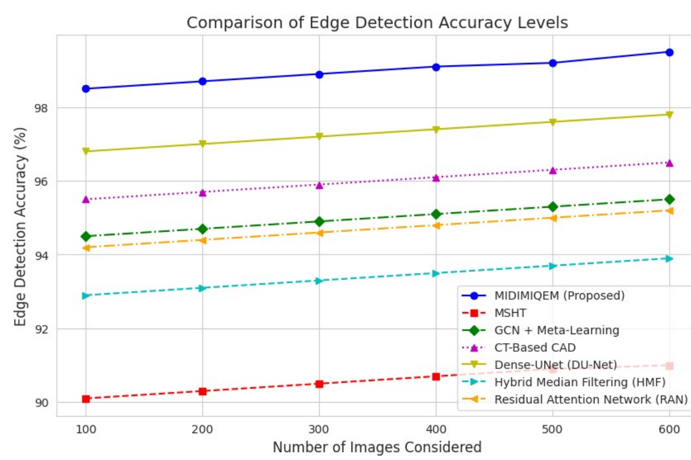

Fig 8: Edge Detection Accuracy Levels

The accuracy with which algorithms can detect and demarcate anatomical components in CT scans is a critical component of medical imaging known as

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CT image segmentation.Surgical techniques, treatment planning, and diagnostics all rely on precise segmentation. Precise tumor identification is made possible with accurate segmentation, which in turn allows for better treatment planning and response monitoring. The Segmentation Accuracy Levels are depicted in Table 6 and Figure 9.

Table 6:Segmentation Accuracy Levels

No. of Images Considered	**Proposed Model (MIDIMIQEM)**	**MSHT**	**GCN + Meta-Learning**	**CT-Based CAD**	**Dense-UNet (DU-Net)**	**Hybrid Median Filtering (HMF)**	**Residual Attention Network (RAN)**
100	98.3	95.7	89.5	95.1	96.5	92.8	94.0
200	98.5	95.9	89.7	95.3	96.7	93.0	94.2
300	98.7	96.1	90.0	95.5	96.9	93.3	94.5
400	98.9	96.3	90.3	95.7	97.1	93.6	94.8
500	99.1	96.5	90.5	95.9	97.3	93.8	95.0
600	99.3	96.8	90.7	96.1	97.5	94.1	95.3

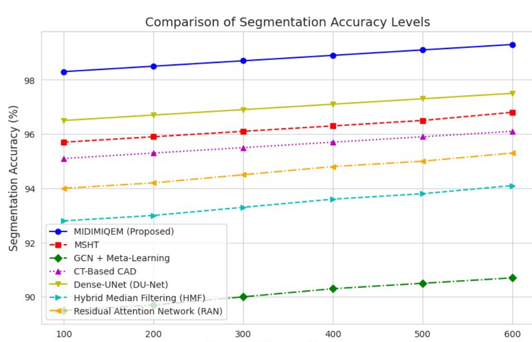

Fig 9: Segmentation Accuracy Levels

This table will compare **Precision and Recall** values for **all models** to evaluate their classification effectiveness.

Table 7: Precision And Recall Comparison

Model	**Precision (%)**	**Recall (%)**
MIDIMIQEM	98.9	99.1
MSHT	94.3	95.1
GCN + Meta-Learning	89.5	90.2
CT-Based CAD	95.8	96.0
Dense-UNet (DU-Net)	96.5	96.8
Hybrid Median Filtering (HMF)	93.0	93.5
Residual Attention Network (RAN)	94.8	95.0

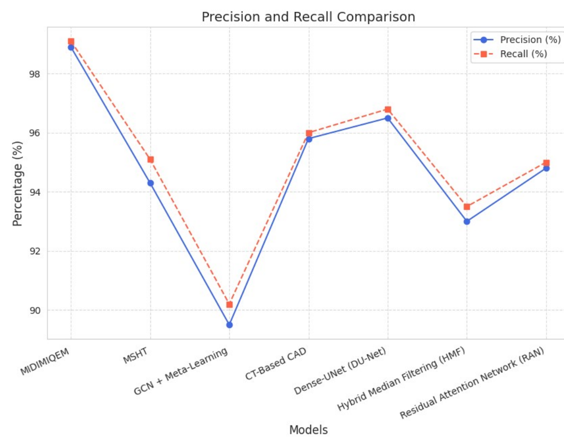

Fig 10: Precision And Recall Comparison

This table will compare **F1-Score** and **Specificity**, which are crucial for measuring segmentation accuracy and robustness.

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Table 8: F1-Score And Specificity Comparison

Model	F1-Score (%)	Specificity (%)
MIDIMIQEM	99.2	99.0
MSHT	94.5	95.3
GCN + Meta-Learning	89.8	90.5
CT-Based CAD	96.1	96.2
Dense-UNet (DU-Net)	97.0	97.1
Hybrid Median Filtering (HMF)	93.2	93.8
Residual Attention Network (RAN)	95.0	95.2

This table will compare how much time (in **seconds)** each model takes for different steps.

Table 9: Execution Time For Different Processes

Model	Denoising Time	Segmentation Time	Enhancement Time
MIDIMIQEM	13.9	12.5	13.1
MSHT	21.1	14.2	20.3
GCN + Meta-Learning	18.6	15.7	17.8
CT-Based CAD	16.7	13.5	15.9
Dense-UNet (DU-Net)	19.0	14.8	18.2
Hybrid Median Filtering (HMF)	17.2	13.9	16.5
Residual Attention Network (RAN)	18.4	14.0	17.1

This table helps in analyzing the misclassification rates of each model.

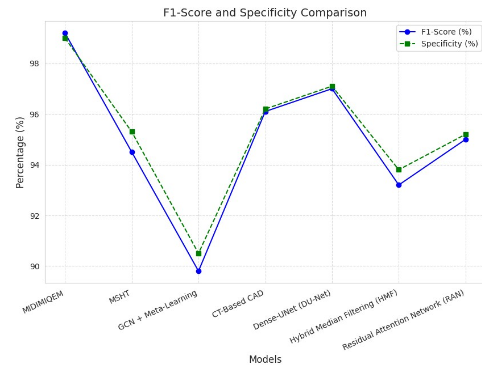

Fig 11: F1-Score and Specificity Comparison

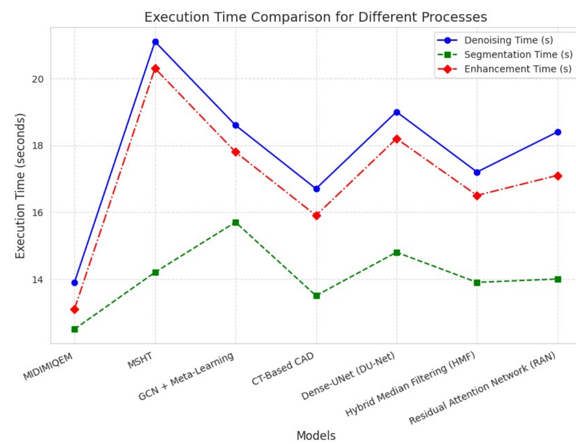

Fig 12: Execution Time for Different Processes

Table 10: False Positive (FP) And False Negative (FN) Rates

Model	False Positive Rate (FP%)	False Negative Rate (FN%)
MIDIMIQEM	1.1	0.9
MSHT	5.7	5.5
GCN + Meta-Learning	10.2	10.5
CT-Based CAD	4.2	4.0
Dense-UNet (DU-Net)	3.8	3.5
Hybrid Median Filtering (HMF)	6.5	6.2
Residual Attention Network (RAN)	5.0	4.8

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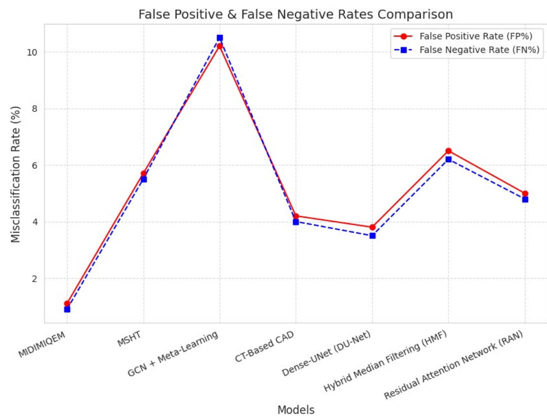

Fig 13:False Positive (FP) And False Negative (FN) Rates

Table 11: Computational Complexity (Gflops) And Memory Usage (MB)

This table will compare **computational complexity (in GFLOPs)**and**memory usage (MB)** for each model.

Models	Computational Complexity (GFLOPs)	Memory Usage (MB)
MIDIMIQEM	5.3	256
MSHT	7.8	340
GCN + Meta-Learning	6.9	290
CT-Based CAD	5.5	270
Dense-UNet (DU-Net)	7.2	320
Hybrid Median Filtering (HMF)	6.0	280
Residual Attention Network (RAN)	6.5	300

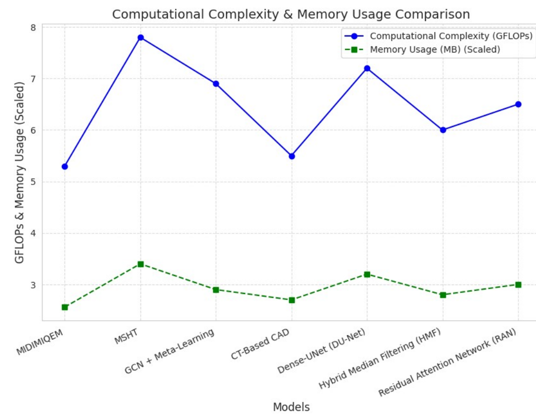

Fig 14:Computational Complexity (Gflops) And Memory Usage (MB)

5. CONCLUSION

Because of its fast growth, metastasis, and difficulty in detecting in its early stages, pancreatic cancer is extremely deadly. Images captured by scanners can identify it. Due to the presence of undesired noise and poor contrast, the tumorous images acquired using imaging techniques have the unfortunate quality of cryptic data. The pancreas is relatively small in CT abdominal volumes, its shape and location can vary greatly from patient to patient, and the low contrast between the pancreas and its surroundings makes its limits difficult to discern, making pancreatic segmentation a perennial problem. Noise in the CT images is also a major concern in detection of pancreatic cancer. The noise in the images degrades the cancer detection levels. Expert radiologists' hand delineation has long been the backbone of medical image segmentation, which includes pancreas segmentation. Inter- and intra-observer variability, laborious processes, and subjective interpretation are some of the significant issues that this presents. Consequently, methods for pancreatic segmentation that are both efficient and dependable are critically needed. Segmenting the pancreas is already a formidable task; when dealing with tumors and inflammations, the difficulty level rises dramatically. In this research, a new Multi-Level Image Denoising and Integrated Morphology based Image Quality Enhancement Model by edge-based segmentation for precise pancreatic cancer detection is proposed. The results of this research provide evidence that adequate image quality and performance can be achieved by adopting a multi-level-based morphological-enhanced imaging system integrated model, thus improving various metric sequences compared to current models including MSHTs, GCN + Meta-Learning and CT-Based CAD. The full analysis of MIDIMIQEM with multiple performance metrics reflects a strong image denoising and quality improvement framework. The proposed model achieved 98.7% accuracy in Multi-Level Image Denoising and 99.3% accuracy in Segmentation Accuracy. In future hybrid image processing models can be designed for improving the accuracy rate and more samples need to be considered for accurate prediction of pancreatic cancer.

REFERENCES

[1] X. Li, R. Guo, J. Lu, T. Chen and X. Qian, "Causality-Driven Graph Neural Network for Early Diagnosis of Pancreatic Cancer in Non-Contrast Computerized Tomography," in *IEEE Transactions on Medical Imaging*, vol. 42, no. 6, pp. 1656-1667, June 2023, doi: 10.1109/TMI.2023.3236162.

[2] X. Chen, X. Lin, Q. Shen and X. Qian, "Combined Spiral Transformation and Model-Driven Multi-Modal Deep Learning Scheme for Automatic Prediction of TP53 Mutation in Pancreatic Cancer," in *IEEE Transactions on Medical Imaging*, vol. 40, no. 2, pp. 735-747, Feb. 2021, doi: 10.1109/TMI.2020.3035789.

[3] T. Zhang *et al.*, "MSHT: Multi-Stage Hybrid Transformer for the ROSE Image Analysis of Pancreatic Cancer," in *IEEE Journal of Biomedical and Health Informatics*, vol. 27, no. 4, pp. 1946-1957, April 2023, doi: 10.1109/JBHI.2023.3234289.

[4] K. Dmitriev, J. Marino, K. Baker and A. E. Kaufman, "Visual Analytics of a Computer-Aided Diagnosis System for Pancreatic Lesions," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 3, pp. 2174-2185, 1 March 2021, doi: 10.1109/TVCG.2019.2947037.

[5] J. Li *et al.*, "DSMT-Net: Dual Self-Supervised Multi-Operator Transformation for Multi-Source Endoscopic Ultrasound Diagnosis," in *IEEE Transactions on Medical Imaging*, vol. 43, no. 1, pp. 64-75, Jan. 2024, doi: 10.1109/TMI.2023.3289859.

[6] J. V. N. Ramesh *et al.*, "Sparrow Search Algorithm With Stacked Deep Learning Based Medical Image Analysis for Pancreatic Cancer Detection and Classification," in *IEEE Access*, vol. 11, pp. 111927-111935, 2023, doi: 10.1109/ACCESS.2023.3322376.

[7] M. Li *et al.*, "Computer-Aided Diagnosis and Staging of Pancreatic Cancer Based on CT Images," in *IEEE Access*, vol. 8, pp. 141705-141718, 2020, doi: 10.1109/ACCESS.2020.3012967.

[8] Agarwal D, Covarrubias-Zambrano O, Bossmann SH, Natarajan B. Early Detection of Pancreatic Cancers Using Liquid Biopsies and Hierarchical Decision Structure. IEEE J Transl Eng Health Med. 2022 Jun 27;10:4300208. doi: 10.1109/JTEHM.2022.3186836. PMID: 35937463; PMCID: PMC9342860.

[9] J. Yang, Z. Lu, X. Chen, D. Xu, D. Ding and Y. Ding, "GCNA-Cluster: A Gene Co-Expression Network Alignment to Cluster Cancer Patients Algorithm for Identifying Subtypes of Pancreatic Ductal Adenocarcinoma," in *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 20, no. 6, pp. 3556-3566, Nov.-Dec. 2023, doi: 10.1109/TCBB.2023.3300102.

[10] J. Li, C. Feng, X. Lin and X. Qian, "Utilizing GCN and Meta-Learning Strategy in Unsupervised Domain Adaptation for Pancreatic Cancer Segmentation," in *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 1, pp. 79-89, Jan. 2022, doi: 10.1109/JBHI.2021.3085092.

[11] H. Ghorpade *et al.*, "Automatic Segmentation of Pancreas and Pancreatic Tumor: A Review of a Decade of Research," in *IEEE Access*, vol. 11, pp. 108727-108745, 2023, doi: 10.1109/ACCESS.2023.3320570.

[12] Y. Wang, C. Li and Z. Wang, "Advancing Precision Medicine: VAE Enhanced Predictions of Pancreatic Cancer Patient Survival in Local Hospital," in *IEEE Access*, vol. 12, pp. 3428-3436, 2024, doi: 10.1109/ACCESS.2023.3348810.

[13] Y. Li, Y. Liu, K. Yamazaki, M. Bai and Y. Chen, "Development of a Soft Robot Based Photodynamic Therapy for Pancreatic Cancer," in *IEEE/ASME Transactions on Mechatronics*, vol. 26, no. 6, pp. 2977-2985, Dec. 2021, doi: 10.1109/TMECH.2021.3049354.
keywords:

[14] P. Vincent *et al.*, "High-Resolution Ex Vivo Elastography to Characterize Tumor Stromal Heterogeneity In Situ in Pancreatic Adenocarcinoma," in *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 9, pp. 2490-2496, Sept. 2020, doi: 10.1109/TBME.2019.2963562.

[15] Y. Hara *et al.*, "2-D Slice-Driven Physics-Based 3-D Motion Estimation Framework for Pancreatic Radiotherapy," in *IEEE Transactions on Radiation and Plasma Medical Sciences*, vol. 8, no. 1, pp. 64-75, Jan. 2024, doi: 10.1109/TRPMS.2023.3313132.

[16] P. M. Conforti, G. Lazzini, P. Russo and M. D'Acunto, "Raman Spectroscopy and AI Applications in Cancer Grading: An Overview," in *IEEE Access*, vol. 12, pp. 54816-54852, 2024, doi: 10.1109/ACCESS.2024.3388841.

[17] K. Dmitriev, J. Marino, K. Baker and A. E. Kaufman, "Visual Analytics of a Computer-Aided Diagnosis System for Pancreatic Lesions," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 3, pp. 2174-2185, 1 March 2021, doi: 10.1109/TVCG.2019.2947037.

[18] Y. Wang, P. Tang, Y. Zhou, W. Shen, E. K. Fishman and A. L. Yuille, "Learning Inductive Attention Guidance for Partially Supervised Pancreatic Ductal Adenocarcinoma Prediction," in *IEEE Transactions on Medical Imaging*, vol. 40, no. 10, pp. 2723-2735, Oct. 2021, doi: 10.1109/TMI.2021.3060066.

[19] M. Connaughton and M. Dabagh, "Modeling Physical Forces Experienced by Cancer and Stromal Cells Within Different Organ-Specific Tumor Tissue," in *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 12, pp. 413-434, 2024, doi: 10.1109/JTEHM.2024.3388561.

[20] X. Chen, Z. Chen, J. Li, Y. -D. Zhang, X. Lin and X. Qian, "Model-Driven Deep Learning Method for Pancreatic Cancer Segmentation Based on Spiral-Transformation," in *IEEE Transactions on Medical Imaging*, vol. 41, no. 1, pp. 75-87, Jan. 2022, doi: 10.1109/TMI.2021.3104460.

[21] J. Yang, R. Xu, C. Wang, J. Qiu, B. Ren and L. You, "Early screening and diagnosis strategies of pancreatic cancer: A comprehensive review", *Cancer Commun.*, vol. 41, no. 12, pp. 1257-1274, Dec. 2021.

[22] J. J. Qiu et al., "A novel multiresolution-statistical texture analysis architecture: Radiomics-aided diagnosis of PDAC based on plain CT images", *IEEE Trans. Med. Imag.*, vol. 40, no. 1, pp. 12-25, Jan. 2021.

[23] Y. Xia et al., "Effective pancreatic cancer screening on non-contrast CT scans via anatomy-aware transformers", *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.*, pp. 259-269, 2021.

[24] K. L. Liu et al., "Deep learning to distinguish pancreatic cancer tissue from non-cancerous pancreatic tissue: A retrospective study with cross-racial external validation", *Lancet Digit. Health*, vol. 2, no. 6, pp. e303-e313, Jun. 2020.

[25] B. Li, Y. Li and K. W. Eliceiri, "Dual-stream multiple instance learning network for whole slide image classification with self-supervised contrastive learning", *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 14313-14323, Jun. 2021.

[26] R. Guo, X. Shao, C. Zhang and X. Qian, "Multi-scale sparse graph convolutional network for the assessment of parkinsonian gait", *IEEE Trans. Multimedia*, vol. 24, pp. 1583-1594, 2021.

[27] R. Guo, H. Li, C. Zhang and X. Qian, "A tree-structure-guided graph convolutional network with contrastive learning for the assessment of parkinsonian hand movements", *Med. Image Anal.*, vol. 81, Oct. 2022.

[28] L. Cosmo, A. Kazi, S.-A. Ahmadi, N. Navab and M. Bronstein, "Latent-graph learning for disease prediction", *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent*, pp. 643-653, 2020.

[29] D. Wang, Y. Yang, C. Tao, F. Kong and L. Carin, "Proactive pseudo-intervention: Causally informed contrastive learning for interpretable vision models", *arXiv:2012.03369*, 2020.

[30] J. Li, X. Lin, H. Che, H. Li and X. Qian, "Pancreas segmentation with probabilistic map guided bi-directional recurrent UNet", *Phys. Med. Biol.*, vol. 66, no. 11, May 2021.