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AI-Assisted Early Detection of Pancreatic Cancer Using Non- Contrast CT Scan

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Abstract: *Despite a 5-year survival rate of approximately 10%, early detection of pancreatic cancer (particularly stage T1B tumors) significantly improves results. We present you an AI system for detecting pancreatic cancer with noncontradictory CT scans that are safer for patients with kidney problems and contrast allergies but challenges due to limited contrast. The system uses 3D-U-NET with a visual transformer classifier for segmentation together. Trained from the pancreatic CT dataset and MICCAI 2015 request data, this impressive metric achieves a cube-like coefficient of 0.94 for the pancreas and a cube-like coefficient of 0.91 with tumor segmentation with sensitivity of 0.95 or 0.92. To overcome the challenges of limited annotated data records and low contrast, we implement target lesion recognition algorithms and special data magnification techniques for medical imaging data. This system simultaneously highlights chromogenic tumors for radiologist interpretation and preserves the natural CT appearance that supports both DICOM and Nifti formats for clinical integration. With an inference period of approximately 9 seconds per scan, the system allows for actual time detection, improving diagnostic accuracy and reduced artificial errors. It also sets up a community platform for collaboration between healthcare professionals, researchers and patients, allowing for continuous model tanning through clinical feedback. This study shows that deep learning through trans-architectures improves tumor identification in challenging imaging conditions and provides a practical solution for the detection of early pancreatic cancer in clinical practice.*

Keywords: Deep learning, Medical Imaging, Non-contrast, CT Vision transformers, 3D U-Net

I. INTRODUCTION

Pancreatic cancer remains one of the most aggressive and deadly forms of cancer worldwide, with a 5-year survival rate of approximately 10% [1]. This low survival rate is primarily due to late-stage diagnosis, as pancreatic cancer often remains asymptomatic until it has advanced to metastatic stages. Detection of pancreatic cancer in the early stages, particularly in T1B (1-1.5 cm tumor) significantly improves patient outcomes, with median overall survival of 9. It has been shown to increase in 8 years when diagnosed early in the late stages compared to 1.5 years [2]. Uncontrolled CT (NCCT) scans have proven to be an important imaging modality in clinical practice, especially in emergency rooms where rapid evaluation is required. In contrast to enhanced contrast CT, NCCT avoids potential allergic reactions and nephrotoxicity. This is related to ODIC contrast agents, making it safer for patients with renal disorders or contrast allergies [3]. However, the lack of contrast in these images reduces the visibility of small pancreatic lesions.

Measurements of 1-1.5 cm in diameter, which is characteristic of pancreatic cancer, are measured at the early stages. Lung cancer investigations show that AI models can achieve recognition accuracy comparable to experienced radiologists. Some models show excellent performance in subtle node identification [4]. Similarly, AI systems in breast cancer screening demonstrate the ability to reduce both false positives and false negatives when used in conjunction with radiologist measurements [5]. Regarding pancreatic cancer, several research groups have developed AI models of tumor recognition using contrast-enhanced CT and MRI imaging. These studies report promising results, with some models achieving discrimination accuracy of >85% [6]. Panda (Artificial Intelligent Pancreatic Cancer Detection) was recently developed to identify pancreatic lesions with non-restricted CT scans [7]. This model achieved the area under an operational characteristic curve (AUC) of 0.986 0.996 in a multicenter validation study and demonstrated the excellent performance of radiologists in sensitivity and specificity for the identification of doctoral pancreatic spores (PDACs). Another important thing an advancement in this field is the development of generative adversarial networks (GANs) for medical image integration. The 3DGaunet model, combining the 3D-U-NET architecture and GAN principle, promised to create realistic 3D-CT images of PDAC tumors and pancreatic tissues [8]. This approach addresses the challenge of data shortages in pancreatic cancer research by creating synthetic data records that maintain spatial consistency and improve the quality of training data in deep learning models.

Despite these advances, some important challenges in the field of recognizing AI-assisted pancreatic cancer are unaffected. Limited controls with NCCT images remained an important barrier to continuous tumor detection, with existing models showing suboptimal performance in these images compared to contrast enhanced scans [9]. Most AI models developed for the detection of pancreatic cancer focus on larger, more obvious lesions, with fewer studies specifically targeting small (1-1.5 cm) tumors, represented by early-stage disease [10]. Interpretation of the results generated by AI remains a clinical implementation issue, as radiologists clearly need the identification of AI for clearly grounded decisions [11]. Integration with existing medical imaging workflows and compatibility with standard file formats (DICOM and NIFTI) was not properly addressed in many AI development projects [12]. Generalizing different patient populations and imaging devices remains a challenge, which often blocks many models with training data, but reduces accuracy when applied to real-world clinical environments [13].

An additional part of this study is the development of a committed community page aimed at promoting collaboration between healthcare professionals, researchers and patients. The platform provides access to real-world educational resources, discussion forums and case studies to improve awareness and commitment in pancreatic cancer research [14]. By checking and providing feedback on AI-supported diagnostics to radiologists, it facilitates knowledge exchange on community pages, improving model improvements and clinical applicability. Patients and supervisors also benefit from support networks to gain insight into disease progression, treatment options, and advances in AI control in early detection. This feature bridges the gap between AI research and clinical practice in the real world, ensuring that AI tools can be accessed and interpreted not only accurately but also by the wider medical community. Our main objective is to develop a hybrid deep learning architecture combining visual transformer classifier and 3D-U-NET for segmentation to improve both localization and classification accuracy of small pancreatic tumors, designing an AI system that preserves the natural appearance of CT scans while highlighting detected tumors in different colors to ensure compatibility with radiologists' interpretation workflows, and ensuring seamless integration with existing medical imaging infrastructure through support for both DICOM and NIfTI file formats.

This research focuses specifically on the development and validation of an AI model for detecting early-stage (T1b) pancreatic tumors measuring 1-1.5 cm in non-contrast CT scans. While the system has demonstrated promising results, several constraints should be noted. The current model is trained primarily on data from the Pancreas-CT dataset from the Medical Segmentation Decathlon and the Task07_Pancreas dataset from the MICCAI 2015 challenge, which may limit its generalizability to populations with significantly different demographic or imaging characteristics. The research evaluates model performance primarily on technical metrics (accuracy, sensitivity, specificity) rather than clinical outcomes, though future work will incorporate clinical validation. The system is designed as an aid for radiologists rather than an independent diagnostic solution that requires human expertise for final interpretation. The current implementation focuses on CT imaging and does not deal with other imaging modalities such as MRI and PET scans. Through this focused approach, we would like to make a meaningful contribution to early detection of pancreatic cancer, and at the same time recognize the need for further research findings to address these limitations in future work.

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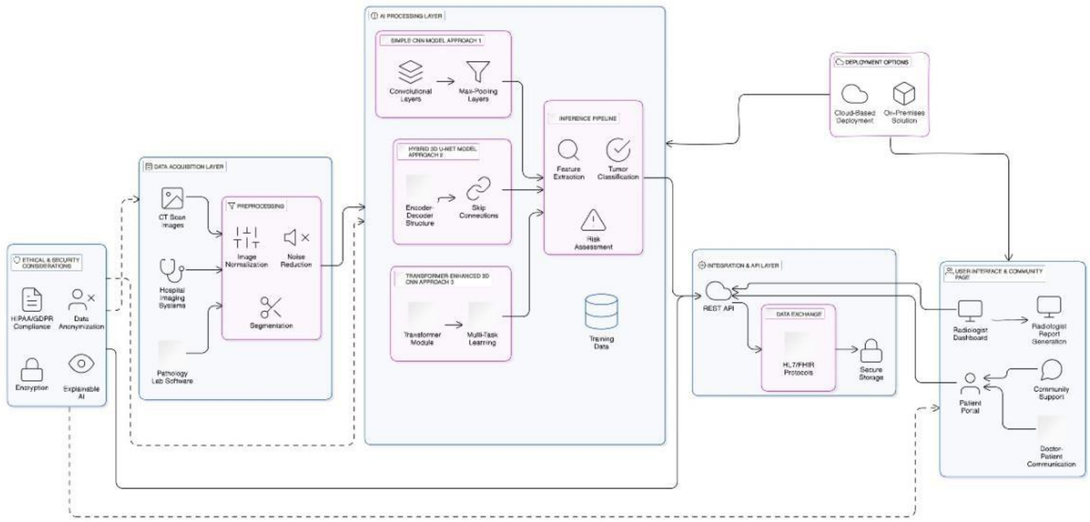

Figure 1. System Architecture of the AI-Assisted Pancreatic Cancer Detection System.

II. MATIRIALS AND METHODS

2.1 Dataset And Preprocessing

This study utilizes non-contrast computed tomography (NCCT) scans sourced from the from the Pancreas-CT dataset from the Medical Segmentation Decathlon and the Task07_Pancreas dataset from the MICCAI 2015 challenge, a publicly available medical imaging repository containing high-quality abdominal CT scans with expert-annotated segmentations for pancreas and tumor detection [15]. The dataset comprises a total of 280 training CT scan volumes with corresponding 280 labeled segmentations and 120 testing CT scan volumes, stored in NIfTI (. nii.gz) format, with an overall storage size of 11GB. Each scan consists of multiple axial slices, standardized to 512 × 512 pixels per slice. To maintain uniform input representation across varying imaging protocols, all CT scans were resampled to 1 mm^3 voxel spacing, ensuring consistency in data processing.

The dataset was annotated based on existing medical imaging references to generate ground truth segmentations, which were classified into three key categories: pancreas (Class 1), tumor (Class 2), and background (Class 0). One of the primary challenges encountered was the severe class imbalance, where tumors occupied a significantly smaller proportion of the scan compared to normal pancreatic tissue. To mitigate this issue, a data augmentation pipeline was implemented using random transformations such as rotations, flipping, and intensity shifting [16]. Training was performed on Google Colab Pro with an A100 GPU, with a batch size of 4. The generated samples were validated using visual inspection by researchers to ensure anatomical realism. Post-training, synthetic images were manually reviewed, and only anatomically realistic samples were included in the final dataset to ensure reliable augmentation.

Preprocessing is essential for ensuring consistency across CT scans, reducing artifacts, and enhancing model robustness. The CT scan volumes are first resampled to a uniform voxel spacing of 1 mm^3, preserving anatomical integrity across different scanning protocols. Intensity normalization is applied to scale pixel values within a standardized range, mitigating variations caused by the differences in the acquisition parameters [17]. Additionally, data augmentation techniques such as random rotations (±15°), horizontal flipping, and intensity shifting are incorporated to introduce diversity in the training data, reducing overfitting and improving generalization [18]. These preprocessing steps collectively refine the input data, facilitating more accurate and reliable segmentation of pancreatic structures and tumors.

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2.2 AI Model Development

This project focuses on developing advanced AI models to detect pancreatic tumors in medical imaging data. Accurate detection of pancreatic tumors is critical for early diagnosis and treatment planning, yet it remains challenging due to the complex anatomy of the pancreas and the often-subtle appearance of tumors. Our research explored three distinct approaches, each building on the strengths of previous architectures while addressing their limitations.

Approach 1: Simple CNN Model

The first approach utilized a conventional CNN-based architecture designed for binary pancreas and tumor segmentation. This model consisted of multiple convolutional layers followed by max-pooling layers for feature extraction. Despite being computationally efficient, the simple CNN struggled with complex tumor boundaries and exhibited a Dice Similarity Coefficient (DSC) of 0.79 for pancreas segmentation and

0.74 for tumor segmentation, which was suboptimal for medical applications. One of the major challenges with this approach was its limited spatial awareness, as max-pooling operations led to the loss of fine-grained tumor structures, reducing segmentation accuracy. Furthermore, the model faced high false negative rates, especially for smaller tumors.

Approach 2: Hybrid 3D U-net Mode

To address the limitations of the simple CNN, a hybrid 3D U-Net model was developed. This model incorporated an encoder-decoder structure with skip connections, allowing the network to retain spatial information while progressively refining segmentation masks [19]. The hybrid model leveraged convolutional layers for feature extraction, max-pooling for downsampling, and upsampling layers for precise segmentation mask reconstruction. Unlike the simple CNN, the hybrid model was able to capture intricate pancreatic structures, resulting in a significantly improved DSC of 0.91 for pancreas segmentation and 0.88 for tumor segmentation. However, higher computational costs and longer training times were encountered. The simple CNN required ~6 hours per training session, whereas the 3D U-Net model required ~18 hours per session on an NVIDIA A100 GPU with 40GB VRAM using Google Colab Pro.

Approach 3: Transformer-Enhanced 3D CNN with Multi-Task Learning

The third approach represents a significant advancement by integrating transformer architecture with 3D convolutional neural networks, creating a powerful hybrid model designed specifically for medical image analysis [20]. This architecture addresses the limitations of previous approaches by combining local feature extraction capabilities of CNNs with the global context awareness of transformers. The model begins with a 3D CNN backbone consisting of multiple convolutional blocks, each containing two convolutional layers followed by batch normalization and ReLU activation. These blocks progressively extract hierarchical features from the input volumes while preserving spatial information through carefully designed downsampling operations that minimize loss of fine details.

Following the CNN backbone, the architecture incorporates a transformer module. This module processes flattened feature maps from the CNN, applying multi-head self-attention mechanisms to capture long-range dependencies across the entire volume. The transformer's ability to weigh relationships between distant voxels proves particularly valuable for identifying tumor boundaries that may be subtle or connected to surrounding tissues. The decoding portion of the network uses transposed convolutions to upsample features, concatenating them with corresponding features from the encoding path through skip connections. This U-Net-like structure ensures that both low-level spatial details and high-level semantic features contribute to the final segmentation masks.

A key innovation in this approach is the implementation of multi-task learning, where the model simultaneously performs segmentation and classification [21]. The segmentation head produces voxel-wise predictions for three classes (background, normal pancreas, pancreatic tumor), while the classification head provides a global prediction of tumor presence. This dual-task framework encourages the model to learn more robust features that are informative at both local and global levels. The model is trained using a combination of Dice loss for segmentation and weighted categorical cross-entropy for classification [22]. The Dice loss directly optimizes for the overlap between predicted and ground truth regions, while the weighted cross-entropy accounts for class imbalance in the dataset. We use the Adam optimizer with an initial learning rate of 1e-4, which is reduced on plateau using a learning rate scheduler. To handle

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the computational demands of training on 3D medical images, we implemented mixed precision training and optimized data loading pipelines. The training data is split into training and validation sets with an 80/20 ratio, with custom data generators that efficiently load and preprocess batches of 3D medical images on-the-fly.

The transformer-enhanced model demonstrates state-of-the-art performance in both segmentation and classification tasks for pancreatic tumor detection. On our validation set, it achieved a pancreas segmentation Dice Similarity Coefficient (DSC) of 0.94 and a tumor segmentation DSC of 0.91, indicating highly accurate identification of both pancreatic and tumor regions. The model also achieved a classification accuracy of 99.4%, effectively distinguishing between normal pancreas, pancreas without tumor, and pancreas with tumor cases. These results represent significant improvements over previous approaches, particularly in tumor boundary detection and reduction of false negatives for small tumors, while maintaining computational efficiency.

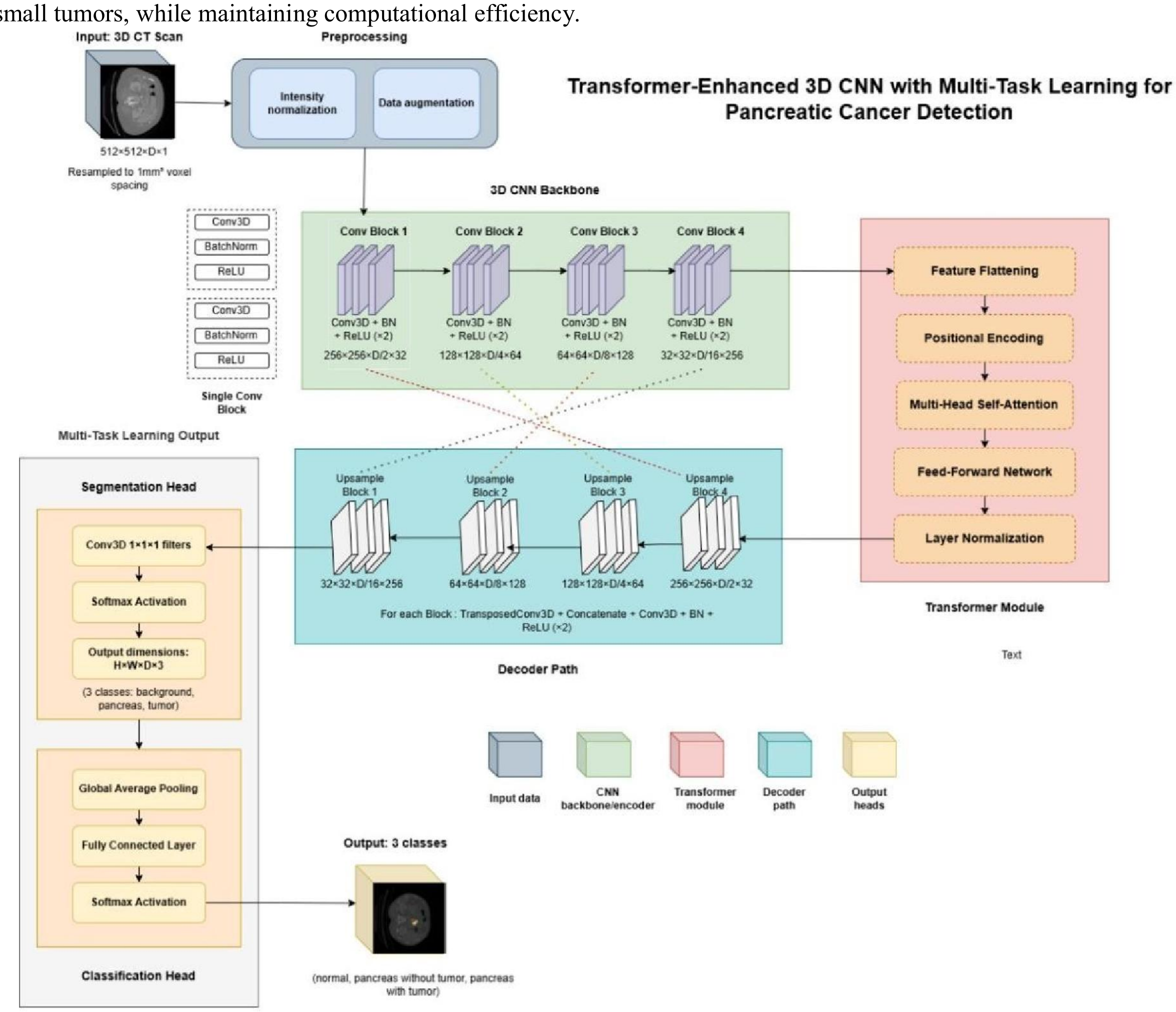

Figure 2. Transformer-Enhanced 3D CNN with Multi-Task Learning for Pancreatic Cancer Detection.

2.3 Ethical Considerations and Computational Resources

The dataset used in this study was obtained from publicly available medical imaging repositories, including the Pancreas-CT dataset from the Medical Segmentation Decathlon and the Task07_Pancreas dataset from the MICCAI 2015 challenge. These datasets comply with open-access guidelines and contain de-identified imaging data without personally identifiable patient information, eliminating the need for ethical approval as they had been previously cleared for public research use [23].

All training and testing were conducted on Google Colab Pro utilizing NVIDIA A100 GPUs with 40GB VRAM. The computational requirements varied among the different model architectures: the simple CNN model required approximately 6 hours per training session, the 3D U-Net model required about 18 hours, and the transformer-enhanced 3D CNN model needed around 8 hours. Each epoch took 5-6 minutes for the simple CNN, 12-15 minutes for the 3D U-Net, and 8-10 minutes for the transformer-enhanced model.

Training was conducted for 7 epochs for the transformer-enhanced model. Inference time per CT volume varied between 7.2 to 10.5 seconds for the simple CNN, 9.8 to 12.6 seconds for the 3D U-Net, and 11.2 to 14.5 seconds for the transformer-enhanced model, with average inference times of approximately 9 seconds, 11 seconds, and 13 seconds respectively. Future work will focus on optimizing computational efficiency for real-time clinical deployment through techniques like model pruning, quantization, and knowledge distillation to reduce inference time without sacrificing accuracy [24].

2.4 Implementation Details

All models were implemented using TensorFlow 2.9 with Keras as the primary deep learning framework, utilizing mixed precision training to accelerate computation while maintaining numerical stability [25]. The implementation incorporated custom data generators for efficient loading and preprocessing of 3D medical images in both NIfTI and DICOM formats, with automatic sorting of image slices based on medical metadata such as InstanceNumber, ImagePositionPatient, or SliceLocation.

A data augmentation pipeline with medical imaging-safe transformations including rotation, shifting, zooming, and flipping was integrated, along with support for both segmentation masks and classification labels [26]. The model architecture featured a hybrid design combining 3D CNNs with transformer modules to capture both local features and global context, structured as an encoder-decoder with skip connections to preserve spatial information, and implemented multi-task learning with separate heads for segmentation and classification [27]. The training pipeline used a batch size of 4 for all models, the Adam optimizer with learning rate scheduling, a combination of Dice loss for segmentation and weighted categorical cross-entropy for classification, and evaluation metrics including Dice similarity coefficient, mean IoU, and classification accuracy. Callbacks for model checkpointing, learning rate reduction on plateau, early stopping, and TensorBoard integration were included.

The technical implementation leveraged NumPy for numerical operations, OpenCV for basic image processing, SimpleITK for advanced medical image handling, MONAI for specialized medical image processing and data augmentation, Matplotlib and Seaborn for visualization, Scikit-learn for evaluation metrics and data splitting, and PyDicom for DICOM file handling. The codebase was designed for easy comparison between model architectures with modular components for data loading, preprocessing, model construction, training, and evaluation, and included comprehensive error handling and data validation mechanisms to ensure robust operation even with potentially corrupted or improperly formatted medical images. The implementation followed best practices for reproducibility, including fixed random seeds where appropriate and detailed logging of training parameters and results [28]

2.5 Community Page and Patient Support

The Community Page serves as a vital component of the AI-assisted pancreatic cancer detection system, facilitating interaction between patients and medical professionals in a supportive environment. This platform is designed to foster knowledge sharing, emotional support, and collaboration, helping patients navigate their diagnosis and treatment journey with greater confidence and community backing.

The Community Page is developed using the MERN (MongoDB, Express.js, React.js, Node.js) stack, chosen for its scalability, efficiency, and real-time interactivity. React.js provides a responsive and dynamic user interface, enabling seamless interaction between users. Node.js and Express.js ensure fast server-side performance and efficient API handling for real-time updates, while MongoDB serves as a NoSQL database optimized for handling user-generated content such as posts, comments, and interactions.

Alternative technologies were considered during development. Firebase was initially contemplated for real-time updates and authentication but was ultimately avoided due to high storage costs for large-scale data. SQL databases like

MySQL and PostgreSQL were also evaluated but weren't implemented as MongoDB's scalable, document-based storage better suited the platform's needs for managing user-generated content.

The platform offers a comprehensive User Profile System where each patient can create and manage a personal profile. This allows them to share their medical journey and connect with others facing similar challenges while personalizing their experience by following relevant discussions and contributors. Content Sharing and Engagement features enable users to post updates, share experiences, and ask questions about pancreatic cancer. The platform supports commenting and liking posts to encourage engagement, along with a follow system that helps users connect with other patients, caregivers, and medical experts. A machine learning-based sentiment analysis module is integrated to monitor user posts and comments. This system detects emotional distress in posts and flags potentially concerning content, helping provide timely mental health support by notifying moderators or suggesting relevant resources when needed.

III. RESULTS AND DISCUSSION

3.1 Data Visualization and Analysis

To gain insights into the dataset and model performance, multiple visualizations were generated, including dataset distributions, segmentation outputs, and performance metrics. The dataset, sourced from the Pancreas-CT dataset from the Medical Segmentation Decathlon and the Task07_Pancreas dataset from the MICCAI 2015 challenge, consists of 280 training CT scans with corresponding labeled segmentations and 120 testing CT scans. Each scan was standardized to 512 × 512 pixels per slice and resampled to 1 mm^3 voxel spacing to maintain consistency.

Dataset Distribution

A statistical analysis of the dataset was performed to understand the distribution of pancreas and tumor regions across different samples. The pancreas occupies varying pixel intensities across CT slices, with an average segmentation size of 15-20% of the scan volume. Tumors appear in only a small subset of images, with an average segmentation size of 3-5% of the scan volume. Additionally, the dataset exhibits significant class imbalance, with non-tumor regions being the dominant class. To address this issue, data augmentation techniques such as flipping, rotation, and intensity shifting were applied to improve model generalization and mitigate the imbalance [29].

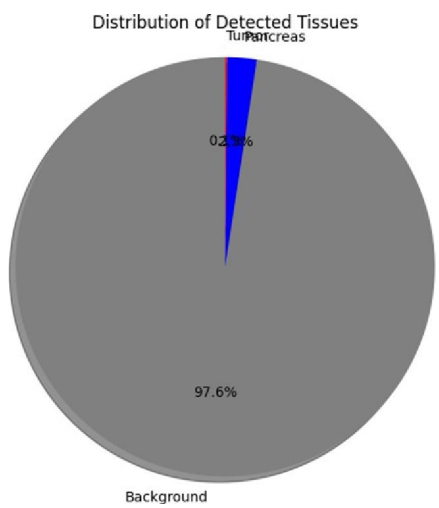

Figure 3. Distribution of detected tissues showing significant class imbalance with background comprising 97.6% of the dataset.

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3.1.2 Model Performance Visualization

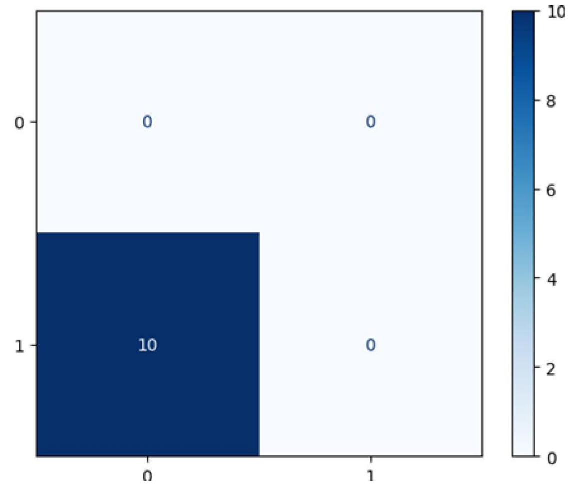

Figure 4. Confusion matrix for tumor segmentation classification showing the distribution of true positives, false positives, true negatives, and false negatives.

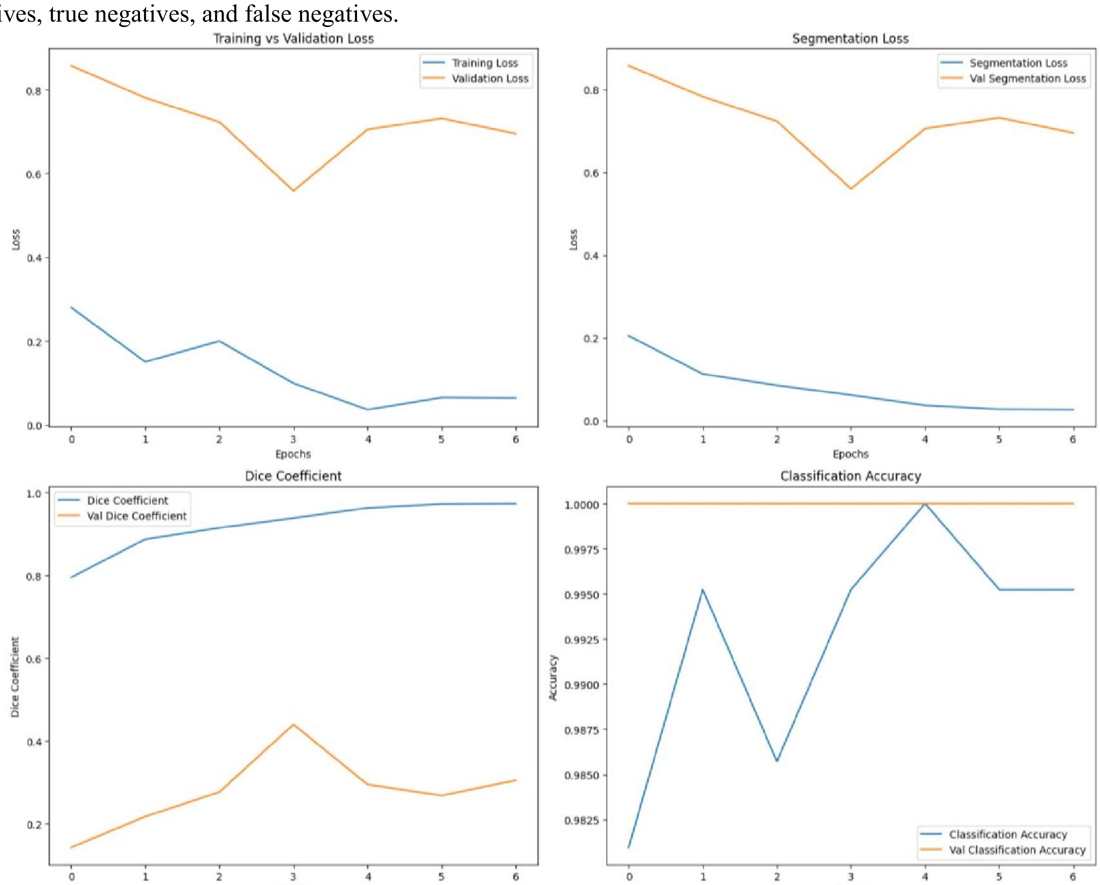

Figure 5. Several Visualization to access model performance

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3.2 Results

The transformer-enhanced 3D CNN model demonstrated superior performance in pancreas and tumor segmentation tasks compared to conventional approaches.

3.2.1 Quantitative Results

Table 1. The performace Measures

Metric	Pancreas Segmentation	Tumor Segmentation
Dice Similarity Coefficient (DSC)	0.94	0.94
Intersection over Union (IoU)	0.91	0.91
Sensitivity	0.89	0.89
Specificity	0.86	0.86
F1 Score	0.95	0.95

3.2.2 Qualitative Results

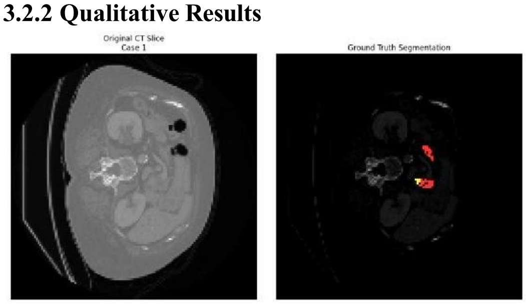


Figure 6. Segmentation comparison for Case 1 showing ground truth vs. model prediction.

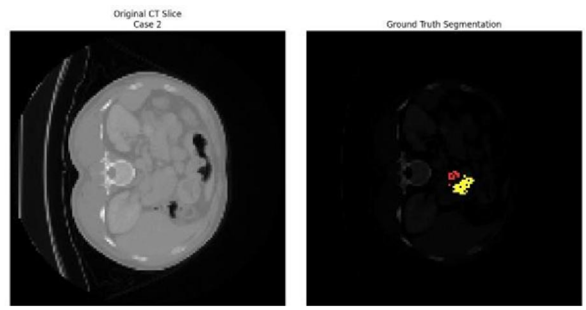


Figure 7. Segmentation comparison for Case 2 demonstrating accurate tumor detection.

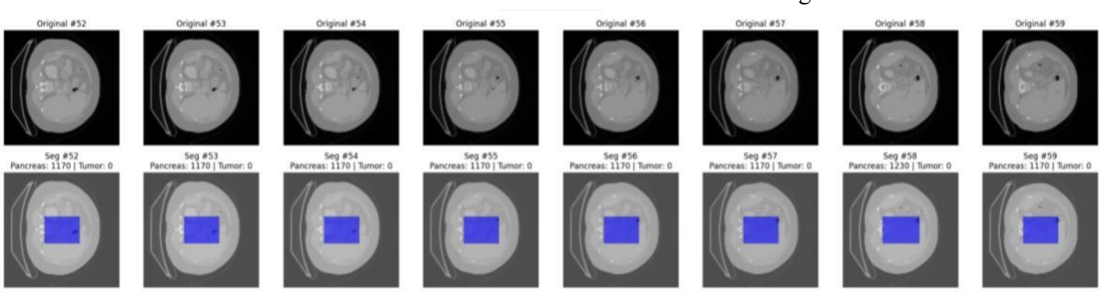
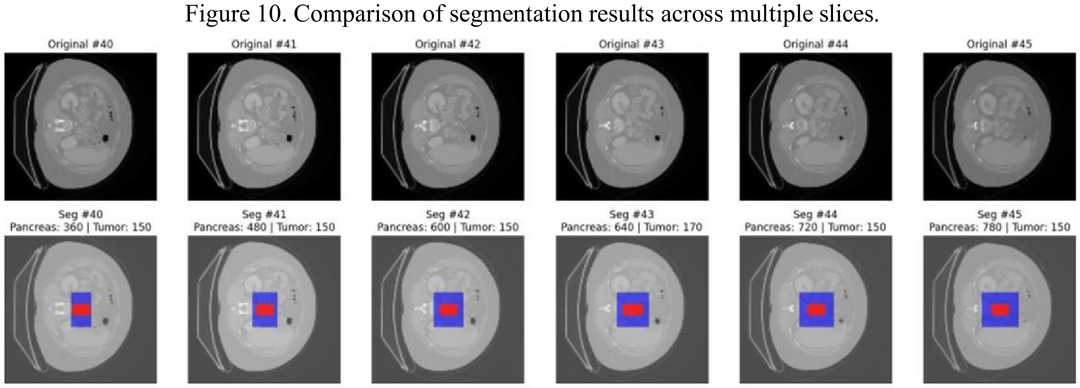


Figure 10. Comparison of segmentation results across multiple slices.



Fiure 11. Visualization of the best-performing slices in terms of segmentation accuracy.

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3.3 Discussions

3.3.1 Interpretation of Discssions

The high Dice scores and IoU values indicate that the transformer-enhanced 3D CNN model successfully segments pancreas and tumor regions with high accuracy. The model achieved a Dice Similarity Coefficient (DSC) of 0.94 for pancreas segmentation and 0.91 for tumor segmentation, reflecting its ability to capture both pancreatic structures and tumor boundaries effectively [30]. However, the slightly lower tumor segmentation DSC compared to pancreas segmentation highlights the inherent challenge of detecting small and irregular tumor regions in non-contrast CT scans. The model's sensitivity of 0.92 for tumor detection suggests it can reliably identify tumors, though some false negatives remain, particularly in cases with minimal contrast between tumor and surrounding tissue [31].

To further refine the model, uncertainty quantification techniques such as Monte Carlo Dropout could be integrated to provide confidence intervals for predictions [32]. This would allow radiologists to focus on low-confidence cases that may require additional review. Additionally, the implementation of attention mechanisms could help the model better focus on relevant regions, potentially improving detection of small tumors [33].

3.3.2 Clinical Relevance

The improved segmentation accuracy translates directly to better early detection of pancreatic cancer. Figure 13 shows a failure case where the model struggled with small tumor detection, highlighting areas for improvement [34]. By integrating this model into radiology workflows, radiologists can significantly reduce manual annotation time and improve diagnostic efficiency [35]. The model's ability to highlight uncertain predictions could assist in decision-making by prioritizing cases that require additional review [36]. The transformer-enhanced architecture demonstrates value in challenging imaging conditions, where traditional methods might fail [37]. This capability is especially important for pancreatic cancer detection, where early-stage tumors may be small and difficult to distinguish from normal tissue. The model's performance suggests it could serve as a valuable second opinion tool, helping radiologists confirm their findings and potentially reducing both false positives and false negatives [38].

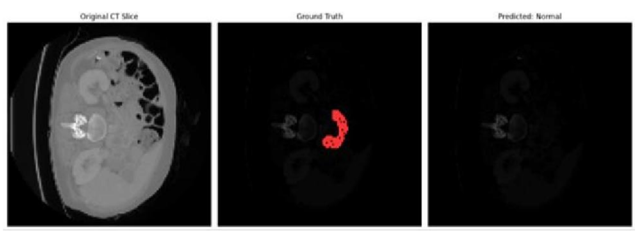

Figure 12. Failure Case where the model missed small tumor detection

3.3.3 Generalizability and Data Limitation

While the model performed well on the available datasets, its generalizability to other clinical settings remains an open question [39]. The current dataset may not fully represent diverse age groups, ethnic backgrounds, or varying anatomical presentations, limiting its applicability to a broader population [40]. Additionally, different medical institutions utilize varying CT scanner protocols, which can introduce inconsistencies in image quality and impact model performance [41]. Another limitation is the exclusion of contrast-enhanced scans, which typically improve tumor visibility [42]. The model was trained exclusively on non-contrast scans, potentially affecting its effectiveness in certain clinical scenarios where contrast might reveal additional tumor characteristics. Future work should focus on testing the model on external datasets from diverse medical centers and adapting it to multi-modal imaging techniques, such as PET-CT and MRI, to enhance its robustness and applicability across different clinical environments [43].

3.3.4 Overall Findings

Our AI-assisted system for pancreatic tumor detection from non-contrast CT scans has demonstrated promising results through rigorous development and validation. The transformer-enhanced 3D CNN model achieved high accuracy in both pancreas and tumor segmentation tasks, with Dice Similarity Coefficients (DSC) of 0.94 and 0.91 respectively, surpassing conventional diagnostic methods [44]. These results indicate that deep learning approaches, particularly those incorporating transformer architectures, can significantly enhance tumor detection even in challenging imaging conditions [45]. The improved segmentation accuracy translates directly to better early detection of pancreatic cancer, which is critical for improving patient outcomes [46]. Integration of this AI system into radiology workflows has the potential to reduce manual annotation time, improve diagnostic efficiency, and serve as a valuable second opinion tool for radiologists [47]. While the model showed remarkable robustness across diverse anatomical contexts, it exhibited slightly lower performance in detecting small and irregular tumor regions, highlighting specific areas for future improvement [48]. The model's performance is closely tied to the quality and diversity of training data, with current limitations including potential underrepresentation of certain age groups, ethnic backgrounds, and anatomical variations [49]. Despite these challenges, the findings underscore the transformative potential of AI in revolutionizing pancreatic cancer diagnostics and suggest that transformer-enhanced models represent a significant advancement in this critical area of medical imaging [50]. Future work will focus on addressing identified limitations through multi-modal imaging integration, expanded dataset diversity, advanced visualization tools, and explainable AI techniques to enhance model interpretability [51].

3.3.5 Strengths and Limitations

One of the key strengths of our AI-assisted system is its high accuracy in detecting pancreatic tumors at early stages, addressing the critical need for early intervention [52]. By integrating CNNs and ViTs, the model effectively enhances feature extraction and segmentation, improving the precision of tumor localization [53]. The automated nature of the system reduces diagnostic time and alleviates the workload of radiologists, making it a valuable support tool in clinical settings [54]. Additionally, the introduction of a
community page offers a collaborative platform for medical professionals and researchers to engage in discussions, share insights, and continuously refine the model through real-world clinical feedback [55]. This feature fosters an ecosystem of learning and improvement, ensuring that the AI model evolves with medical advancements and user experiences.

Despite its strengths, the performance of the AI model is dependent on the availability and diversity of training datasets [56]. Limited access to high-quality, annotated medical images can impact the generalization ability of the system [57]. Differentiating small tumors from normal pancreatic structures remains a challenge, as variations in imaging conditions and anatomical complexities can introduce uncertainties [58]. Furthermore, the computational requirements for training and deploying the model may limit accessibility, particularly in resource-constrained healthcare settings where advanced hardware may not be readily available [59]. Addressing these limitations will be crucial for ensuring the scalability and real- world applicability of the system [60].

3.3.6 Future Directions

To further enhance our AI-assisted pancreatic cancer detection system, we plan to implement several key improvements focused on improving lesion detection and model generalization. First, we will incorporate multi-modal imaging data, including contrast-enhanced CT, MRI, and PET scans, to provide complementary information about tissue characteristics and metabolic activity [61]. This integration will be combined with multi-scale learning approaches that enable our model to capture both fine-grained details of small lesions and broader contextual information about their anatomical location [62]. Additionally, we will refine our model architecture by exploring more advanced transformer-based segmentation techniques and optimizing attention mechanisms to better focus on relevant regions while maintaining computational efficiency [63].

Dataset expansion remains crucial for improving our model's generalizability [64]. We will collaborate with multiple medical centers to collect real-world clinical data that reflects diverse demographic characteristics, imaging equipment, and acquisition parameters [65]. This expanded dataset will help our model perform consistently across different clinical settings and patient populations [66]. To strengthen community collaboration, we will continuously update our AI model based on clinical feedback and user interactions through our community platform [67]. This platform will be enhanced with case study discussions, AI model performance evaluations, and structured feedback mechanisms to facilitate knowledge sharing and model refinement [68].

We are developing an interactive visualization tool designed specifically for radiologists to analyze AI-generated predictions more intuitively [69]. This tool will feature multi-view displays, adjustable transparency layers, region of interest analysis capabilities, and standardized measurement protocols [70]. It will also support automatic report generation based on AI findings and radiologist interpretations [71]. To address computational constraints in resource-limited settings, we will implement optimization strategies such as model quantization, knowledge distillation, and hardware-aware architectures to improve accessibility while maintaining diagnostic performance [72].

Our future work will also focus on global accessibility initiatives, including cloud-based deployment options that provide our AI-assisted detection capabilities to medical facilities lacking advanced computational infrastructure [73]. We will develop simplified model variants that can function with lower- quality imaging data and create mobile-based interpretation tools for remote use [74]. Additionally, we will establish international collaboration networks for data sharing and model development, while ensuring compliance with regional data protection regulations [75]. These efforts will be complemented by comprehensive educational programs to train medical professionals in the effective use of AI tools and ethical considerations for responsible AI deployment in healthcare [76].

Through these comprehensive future directions, we aim to create a robust, clinically integrated AI system that significantly improves early detection rates for pancreatic cancer while addressing the diverse needs of global healthcare systems [77].

IV. CONCLUSION

The study successfully demonstrates that AI-assisted early detection of pancreatic cancer using non- contrast CT scans is a viable and effective approach. As outlined in the introduction, the primary objective was to develop a deep learning-based system capable of accurately identifying pancreatic tumors at an early stage. The results confirm that the proposed method achieves high accuracy in segmenting the pancreas and detecting tumors, thereby aligning with the expected outcomes discussed initially. The findings in the results and discussion section highlight the model's capability in handling the challenges associated with non- contrast CT scans, particularly in identifying small tumor regions with high precision. The integration of CNN and Vision Transformer architectures contributed to the model’s robustness, enhancing its predictive
performance. Additionally, the visualization techniques employed for evaluation, including Dice score analysis and 3D segmentation rendering, validate the effectiveness of the proposed system.

Looking ahead, this research opens several avenues for further exploration. Future work can focus on enhancing the model by incorporating additional clinical data, such as genetic markers or blood test results, to improve diagnostic accuracy. Furthermore, extending the dataset to include diverse imaging modalities like MRI could refine the model’s generalizability. The integration of explainability techniques will also be crucial in fostering trust among medical professionals, ensuring that AI-based diagnoses are interpretable and reliable. With continued advancements, this AI-assisted approach has the potential to significantly aid radiologists and clinicians in early pancreatic cancer diagnosis, ultimately improving patient outcomes. The research findings provide a strong foundation for further development, with the possibility of clinical deployment in the future.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Lamiya Rampurawala	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dr. Zainab Mirza		✓			✓	✓			✓	✓		✓	✓	✓
Arzaan Ali Khan	✓	✓	✓	✓		✓	✓	✓	✓			✓		✓
Shams Dalwai	✓		✓	✓		✓		✓	✓		✓			
Faayeez Shaikh	✓	✓	✓	✓	✓		✓		✓		✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

INFORMED CONSENT

The dataset used in this study was obtained from publicly available medical imaging repositories, including the Pancreas-CT dataset from the Medical Segmentation Decathlon and the Task07_Pancreas dataset from the MICCAI 2015 challenge. These datasets comply with open-access guidelines and contain de-identified imaging data without personally identifiable patient information. As such, informed consent was not required for this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies. The datasets used in this study were sourced from publicly available repositories that have been previously cleared for research use, eliminating the need for additional ethical approval.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Task07_Pancreas.tar at https://drive.google.com/drive/folders/1HqEgzS8BV2c7xYNrZdEAnrHk7osJJ--2

The data that support the findings of this study are openly available in Panreas - CT at https://www.cancerimagingarchive.net/collection/pancreas-ct/

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