DESIGN OF A CNN-BASED EXTRACTOR FOR OPTIMAL CLASSIFICATION OF PANCREATIC CANCER

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ABSTRACT

This study presents a Convolutional Neural Network (CNN) based extractor for the automated tracking and detection of pancreatic tumors using a combination of CNN, as a feature extractor, ResNet and Region Proposal Networks (RPN) for classification tumor localization in CT images. The proposed system aims to enhance diagnostic accuracy and assist radiologists in identifying early-stage tumors. The methodology used is Agile. The total sample size of data collected for the study is 2057 CT images of PC from Nnamdi Azikiwe University Teaching Hospital (NAUTH), Awka, Anambara state. Proposed CNNs with multi scale convolutional process was applied for to extract relevant features from CT scan images. The extracted features were applied to train ResNet as the classifier, while RPN is then used to detect potential regions of interest where tumors might be present. The combined model is evaluated on a pancreatic cancer dataset, where various metrics such as F1-score, precision, recall, and confusion matrices are used to assess its performance. The model achieved an F1-score of 0.97 with a confidence threshold of 0.395 and a recall of 1.0 at the same threshold. The confusion matrix indicates a 93% correct prediction for tumors, with the rest categorized under background and no-tumor classes. The mAP score, a key metric for object detection models, improved significantly from 0.1973 to 0.85331, demonstrating the model's robustness in identifying tumors. These metrics suggest a highly accurate model capable of distinguishing between tumor and non-tumor regions, minimizing false positives and false negatives.

Keywords: Pancreatic Cancer; Convolutional Neural Networks (CNN); ResNet; Region Proposal Networks (RPN); Deep Learning

1. INTRODUCTION

Pancreatic Cancer (PC) is a type of cancer that originates in the cells of the pancreas, which is an organ located in the abdomen behind the stomach (Althobaiti et al., 2022). This type of cancer is known to be aggressive and often spreads rapidly to nearby organs and tissues, as well as distant organs such as the liver, lungs, and bones. According to Bowen (2022), PC is among the deadliest of all cancer diseases, with only 11% of its victim surviving after the first five years of infection. The PC is Pancreatic cancer encompasses different types based on the specific cells and structures within the pancreas that are affected. The two main types of pancreatic cancer are exocrine tumors and endocrine tumors. Exocrine tumors are the most common and account for the majority of pancreatic cancer cases. The most prevalent subtype of exocrine tumors is adenocarcinoma, which arises from the cells lining the pancreatic ducts. Adenocarcinoma is known for its aggressive nature and is associated with a poor prognosis, thus making the centre of this research. Endocrine tumors, also known as neuroendocrine tumors, are relatively rare and arise from the endocrine cells of the pancreas (Arulmozhi et al., 2020).

According to Hameed and Krishnan (2022), PC has remained a very big medical challenge to diagnose. This is because the pancreas is a small body organ deeply seated in the retro-peritoneal organ and surrounded by other complex body organs such as the liver, intestine, and stomach. In addition, the American Cancer Society (ACS) report in 2021 and the National Cancer Institute (NCI) report in 2021, also submitted that other factors which make the treatment of PC difficult are lack of early symptoms, rapid disease progression, absence of effective screening system and similar symptoms with other health conditions (these symptoms are only experienced at the later stage), anatomical challenge and complexity of PC which consist of many diseases with varying characteristics to form the tumor (ACS, 2021; NCI, 2021).

Artificial Intelligence (AI) has recorded several breakthroughs in many fields including medicine. It is a computer algorithm that can solve difficult task with high accuracy potential and have been applied to solve medical -related challenges (Antonio et al., 2021). Machine Learning (ML) is a branch of AI with algorithms such as K-Nearest Neighbour (KNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), Naïve Bayes (NB), Decision Tree (DT), etc, that can be trained with data to generate models capable of solving the problem (Tang et al., 2018).

According to Arulmozhi et al. (2020), CNN which is a type of ANN has dominated the application of neural networks for the classification of medical imaging. Watson et al. (2020) used CNN to train PC data captured with CT scan and achieved 0.785 success. Mu et al. (2020) also applied a similar strategy and recorded 0.89. In addition, Liu et al., (2019) used the same strategy for PC classification and reported 0.9632. However, Althobaiti et al. (2022) argued that the variable characteristics of PC attributes affect the learning efficiency of models for PC classification.

The traditional feature extraction section of CNN which is the pooling layer suffers many technical limitations such as loss of spatial information, reduced discriminative ability, limited adaptability, inherently non-interpretability (Zafar et al., 2022). To address this Chan et al. (2020) used a spatial features extraction approach instead and then classifier of multiple hyper-spectral data with CNN to produce 98.79% accuracy. Data segmentation (Men et al., 2017; Fu et al., 2018), and capsule network extractions (Althobaiti et al., 2020), as optimize for CNN extractors, but despite the success, the researcher suggest that these approaches may not be the best to guarantee optimal PC detection by CNN as they are not strategic and will not provide the best extraction result. Therefore, this paper proposed a strategic feature extraction approach to optimize the performance of CNN training for the tracking and detection of PC.

1.1 RESEARCH METHODOLOGY

The methodology used for this research is Agile, a dynamic and iterative approach that emphasizes flexibility, collaboration, and customer-centricity in project management and software development. Agile methodologies allow teams to adapt to changing requirements and respond swiftly to feedback, facilitating continuous improvement throughout the project lifecycle. In this study, the Agile framework was employed to promote incremental progress in the development of the pancreatic cancer classification model. This involved breaking down the project into smaller, manageable tasks or sprints, each focusing on specific aspects of the model, such as data collection, preprocessing, feature extraction, and model training. Regular meetings, known as stand-ups, were held to assess progress, address any challenges, and realign objectives as necessary. The iterative nature of Agile allowed for frequent testing and validation of the model, ensuring that adjustments could be made based on performance metrics and validation results at each stage. By prioritizing collaboration among cross-functional teams, including data scientists, domain experts, and software engineers, the methodology fostered an environment conducive to innovation and rapid problem-solving. This approach ultimately led to the development of a robust classification model that effectively meets the project's goals of accurately detecting pancreatic cancer in medical imaging.

1.2 Data collection

The data collection for this study was from Madeley online data source as the primary source of data collection. The data sample size 2000, considering 210 patients undergoing first-line surgery for Pancreatic Ductal Adenocarcinoma (PDA), utilizing preoperative Magnetic Resonance Imaging (CT). Patients considered for the data collection re from the age of 25 till 75years, while considering the four stages of PDA. The secondary source of data collection is Nnamdi Azikiwe University Teaching Hospital (NAUTH), Awka, Anambara state. The sample size of data is 57CTof 5 patients with PDA. the data was used or the testing and experimental validation of the new system. The total sample size of data collected is 2057 CT images of PC.

1.3 Data processing

The data processing method used for the CT image is the normalization method (Rukundo, 2023). The normalization technique applied is the fixed window strategy (Albert et al., 2023). This CT normalization method involves transforming the pixel intensity values of the CT images to a standardized scale, ensuring uniformity for analysis and visualization. In the process the fixed window size is determined based on predefined parameters, typically a window width and window level. The window width defines the range of pixel values to be considered, while the window level sets the centre of this range. This facilitates feature comparison between different images and enhances the

interpretability of the CT data for feature extraction.

1.4 Convolutional neural network (CNN)

The convolutional neural network was used for the feature extraction process, applying specialized components of the network such as the convolutional layer, kernel filter and pooling layers to extract the intricate features of the CT pancreatic cancer data and then fusion for training purposes. The CNN has four main layers which are the input layer, convolutional layers, fully connected layer and output layer. The inut layer dimensioned the images, then the convolutional layer applied hierarchical spatial pooling and filters to perform convolutional scan on the image and then extract the feature vectors for concatenation and then formation of the convolutional layer. This process continued until the final convolutional layer white the feature mass concatenated are flattened and forward to the fully connected layer which fusion the features for training purposes.

1.5 Residual Network (ResNet)

The ResNet is a deep learning techniques which used residual network to address training complexities experienced with the traditional deep learning techniques (Xu et al., 2020; Hindarto, 2023). The ResNet is made of residual blocks which used convolutional layers, rectified linear unit and batch normalization process to learn feature maps and generate the PC model. The residual block has skip connections which facilitates fast skipping of the neurons while allowing gradients to slow more effectively and easy training of deep neurons.

1.6 Region proposed Network (RPN)

The RPN was used to identify the image part with PC predicted by the ResNet and the assign bounding box to localize the PC. This is achieved utilising region of interest pooling and final prediction head to obtain the final classified images and bounding box coordinates for pancreatic cancer tracking. The integration of RPN with ResNet enhances the overall performance of bounding box prediction. ResNet's ability to capture complex patterns and representations enables the RPN to make more informed predictions about potential pancreatic cancer within the CT image

2. TRAINING OF THE RESIDUAL NETWORK (RESNET)

To train the ResNet, back-propagation training algorithm was applied to train the network. The training algorithm adjusted the hyper-parameters of the ResNet such as depth which determines the size of the ResNet Layers which in this case is ResNet-101, number of filter channels, skip connections, learning rate, batch size, and weight initialization parameters. During the training process, each of these hyper-parameters are adjusted and the model performance monitored considering such as accuracy and gradient loss until the best learning performance for the parameters are recorded, then the training stops and generate the model for the Pancreatic cancer tracking and detection.

2.1 Pancreatic cancer tracking and detection model

Pancreatic cancer tracking and detection model is the output of the ResNet training process. The model forms the foundation for the tracking and classification of PC features when a s test CT image is loaded. To model first applied the HSP to extract the feature maps of the loaded image, and then match with the trained ResNet. When the trained feature corresponds with the import CT image features, the section of the CT uses bounding box prediction to label the segment with the PC.

2.2 Control Centre/Main Menu

In this section, we present the control centre diagram for our pancreatic cancer classification model, which integrates a CNN extractor, ResNet, and a Region Proposed Network (RPN). The model workflow begins with input CT of the pancreas, where the CNN extractor performs feature extraction. This initial extraction captures essential spatial features through convolutional layers, filtering the images for cancer-relevant data. Next, ResNet is used for deeper feature extraction, leveraging residual connections to prevent vanishing gradients and improve model performance. The RPN then identifies potential regions of interest (ROIs) where cancerous tumors may be located. Finally, these ROIs are classified into malignant or benign categories, generating a precise output for cancer detection. This layered approach ensures efficient detection, robust feature extraction, and accurate classification, essential for early pancreatic cancer diagnosis. Figure 1 presents the control centre diagram.

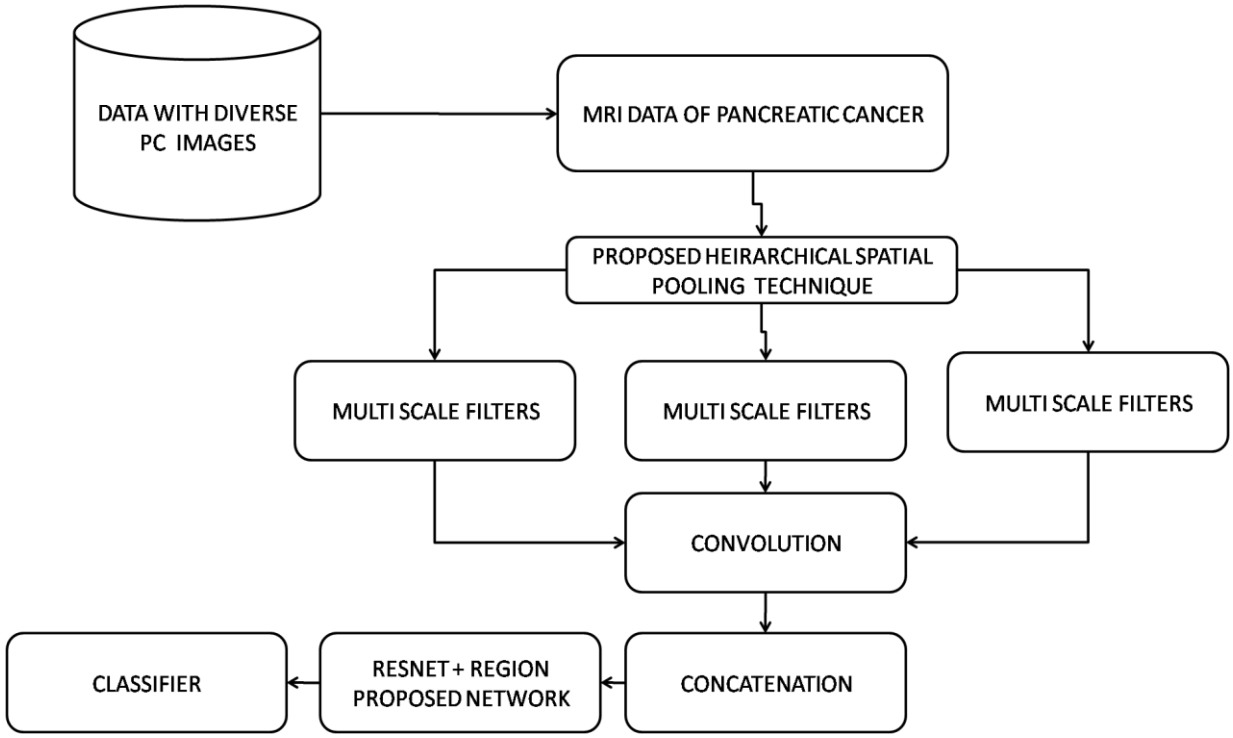

Figure 1: Control centre diagram

3. SYSTEM IMPLEMENTATION

The implementation of the pancreatic cancer classification system involved several key components, leveraging Python and popular machine learning libraries to create a robust solution. Initially, the system was designed to facilitate the seamless input of patient data and medical images. A data input module was established, where patient information was gathered from CSV files, and images were processed using OpenCV for resizing and normalization. The images were then fed into a Convolutional Neural Network (CNN) and ResNet model, which had been pre-trained on relevant medical datasets. This allowed for efficient feature extraction, capturing the intricate patterns and characteristics of the images indicative of pancreatic cancer. Subsequently, a Region Proposal Network (RPN) was integrated to identify and classify regions of interest within the medical images. The outputs from the RPN were classified as either malignant or benign using the classification model, generating a probability score to indicate the confidence level of each prediction. The system was also equipped with a database management module to store patient details, image metadata, and classification results in an organized manner. Finally, a reporting module was implemented to generate detailed diagnostic reports in PDF format, summarizing the classification results along with patient information. This structured approach ensured a comprehensive solution for pancreatic cancer classification, facilitating timely and informed clinical decisions. The successful implementation of the pancreatic cancer classification system relies on specific hardware and software requirements to ensure optimal performance and efficiency.

4. SYSTEM RESULTS AND DISCUSSION

This section presents the results of the model developed in this work for the classification of PC. First the training result of the ResNet + RPN was evaluated using metric such as precision, recall, and loss functions at different epochs. Upon convergence of the scores, the training stops and generated the model for PC classification. The Table 1 and 2 presents the training results.

Table 1: Training result of the ResNet + RPN

Epoch	train/box_loss	train/ cls_loss	train/ dfl_loss	metrics/ precision(B)	metrics/ recall(B)	metrics/mAP50(B)

1	1.3002	2.1621	1.3797	0.40135	0.38805	0.33896
2	1.1476	0.9414	1.2375	0.86879	0.7102	0.82171
3	1.0536	0.7564	1.1779	0.62036	0.64397	0.6486
4	1.0172	0.71022	1.1555	0.81648	0.82228	0.86424
5	0.94493	0.62662	1.1059	0.8713	0.8159	0.89867
6	0.87226	0.53168	1.0689	0.92277	0.83347	0.92072
7	0.81186	0.49267	1.0344	0.94414	0.92746	0.97082
8	0.77343	0.44689	1.0161	0.93364	0.95146	0.97558
9	0.72512	0.39803	0.98387	0.95924	0.96045	0.98026
10	0.67191	0.36031	0.95063	0.96562	0.96957	0.98944

Table 2: Training result of the ResNet + RPN Cont

epoch	metrics/mAP50-95(B)	val/box_loss	val/cls_loss	val/dfl_loss	lr/pg0	lr/pg1	lr/pg2
1	0.1973	1.7121	3.9586	1.7958	0.000551	0.00055139	0.000551
2	0.55547	1.0154	0.98139	1.1944	0.000997	0.00099746	0.000997
3	0.41983	1.2833	1.3236	1.4372	0.001334	0.0013335	0.001334
4	0.57605	1.0054	0.80564	1.1825	0.001172	0.0011719	0.001172
5	0.67028	0.84207	0.72505	1.1014	0.001172	0.0011719	0.001172
6	0.68063	0.80489	0.64695	1.0725	0.001007	0.0010069	0.001007
7	0.7688	0.72188	0.47663	1.0147	0.000842	0.00084184	0.000842
8	0.78032	0.71733	0.41932	1.0093	0.000677	0.0006768	0.000677
9	0.83278	0.58658	0.34997	0.94151	0.000512	0.00051177	0.000512
10	0.85331	0.55188	0.32721	0.92047	0.000347	0.00034674	0.000347

The training results for the pancreatic cancer classification model showcase the model's performance across ten epochs, highlighting key metrics such as box loss, classification loss, distribution focal loss (DFL), and performance indicators like precision, recall, mean average precision (mAP50), and mAP50-95. These metrics provide insight into how the model improves its localization of cancerous regions, its ability to classify malignant and benign cases, and how well it generalizes to unseen validation data.

4.1 Performance Metrics

Precision: This metric measures how many of the predicted cancerous regions were correctly classified as cancerous. The precision improves dramatically from 0.40135 in epoch 1 to 0.96562 by epoch 10. This increase indicates that the model becomes more reliable at correctly identifying true positives (malignant regions) as training progresses, reducing false positives over time.

Recall: Recall measures how many of the actual cancerous regions were correctly identified by the model. The recall improves significantly, rising from 0.38805 in epoch 1 to 0.96957 in epoch 10. A high recall suggests that the model successfully identifies almost all malignant regions, minimizing the chances of missing true cancerous areas, which is critical in medical diagnostics.

mAP50 and mAP50-95: These metrics evaluate the overall detection performance of the model. The mAP50 (mean average precision at 50% intersection over union threshold) increases from 0.33896 in epoch 1 to 0.98944 by epoch 10, indicating a near-perfect detection capability by the end of training. The mAP50-95 (averaged across a range of IoU thresholds) shows substantial improvement, rising from 0.1973 to 0.85331, reflecting the model's ability to detect cancerous regions with high precision across various confidence thresholds. Throughout the training process, the learning rate is reduced gradually, which is a common strategy to ensure stable learning as the model converges. The learning rate starts at 0.00055139 in epoch 1 and decreases to 0.00034674 by epoch 10 across all parameter groups (pg0, pg1, pg2). This gradual reduction ensures that the model makes smaller, more refined adjustments to its

parameters as training progresses, helping prevent overshooting and improving convergence. The figure 2 presents the training graphs plotted with the table 9 and table 10 respectively.

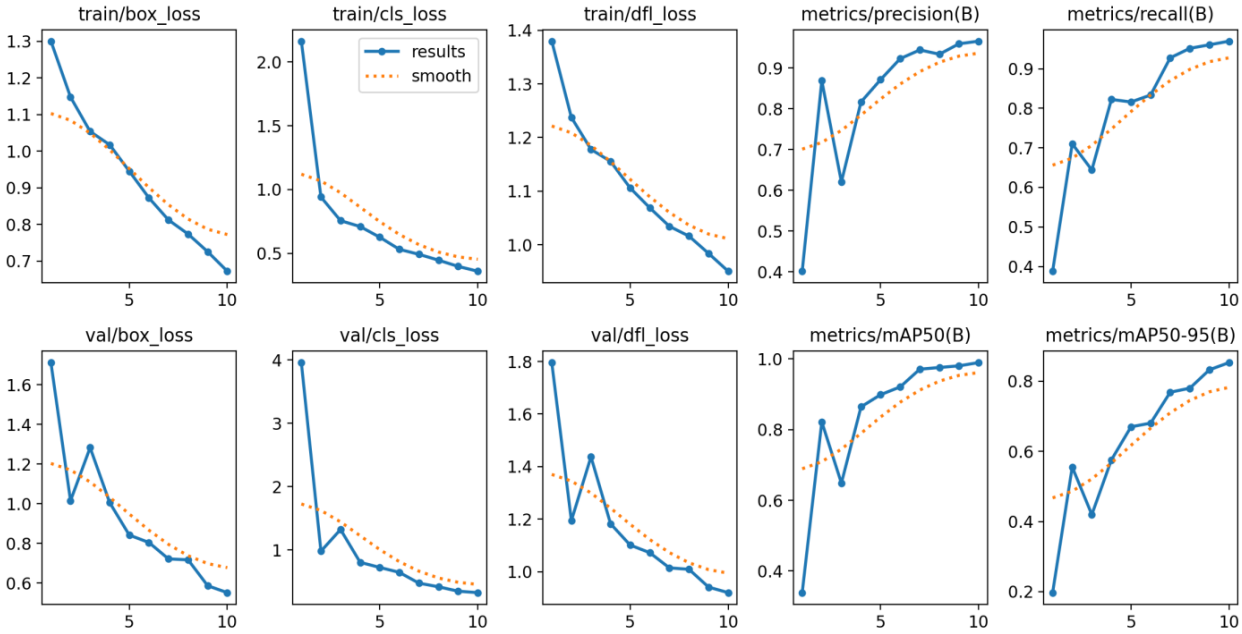

Figure 2: Graphs of the training results

The training results in Figure 2 for the pancreatic cancer classification model, combining ResNet and RPN, demonstrate significant improvements over 10 epochs. The training box loss decreased from 1.3002 to 0.67191, and the training classification loss reduced from 2.1621 to 0.36031, indicating better localization and classification performance. The validation box loss dropped from 1.7121 to 0.55188, and the validation classification loss fell from 3.9586 to 0.32721. Precision improved from 0.40135 to 0.96562, while recall increased from 0.38805 to 0.96957. The mAP50 rose from 0.33896 to 0.98944, and mAP50-95 improved from 0.1973 to 0.85331, reflecting the model's enhanced ability to detect cancerous regions with high accuracy as training progressed. The confusion matrix in Figure 3 presents the model classification accuracy.

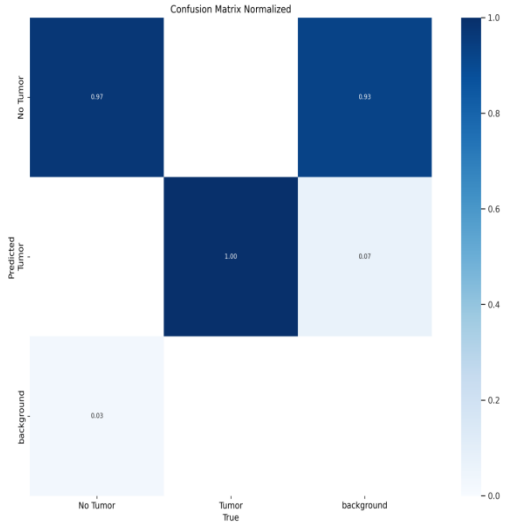

Figure 2: Confusion matrix results

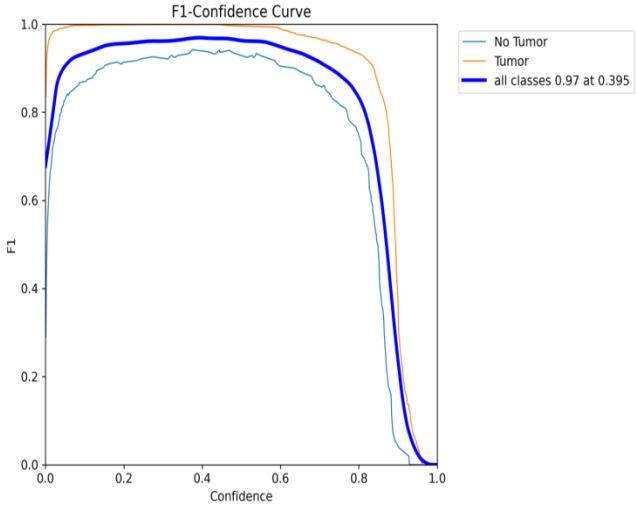

Figure 3: F1-Confidence score

The confusion matrix in Figure 2illustrates the performance of the classification model for pancreatic tumor detection, revealing strong accuracy across the key classes: "No Tumor," "Tumor," and "Background." The model achieved a remarkable 97% accuracy for the "No Tumor" class, indicating that 97% of actual no-tumor cases were correctly

identified. Furthermore, the model excelled in classifying tumor cases, achieving a perfect score of 1.00 for true positives, meaning that there were no false negatives in this category. However, there were some misclassifications concerning the background class, with values of 0.03 for no tumor and 0.07 for tumor. Overall, these results demonstrate that the model is highly effective in distinguishing between tumor and no tumor cases, while it faces slight challenges in accurately classifying the background, underscoring its potential as a reliable diagnostic tool in clinical applications for pancreatic cancer detection. Figure 3 presents the F1-confidence curve for the classification performance for tumor and no tumor.

The F1-Confidence curve demonstrates the performance of the model across varying confidence thresholds for both tumor and no-tumor classes. The orange line (representing the tumor class) consistently maintains a higher F1 score across the confidence range, peaking close to 1, showing the model's strong ability to identify tumors correctly with minimal false positives or false negatives. The blue line (no-tumor class) performs slightly lower but is still high, indicating the model also performs well in identifying non-tumor regions. The curve for all classes peaks at 0.97 F1 at a confidence threshold of 0.395, suggesting that this threshold provides an optimal balance of precision and recall. This threshold is considered optimal because, at this point, the balance between precision and recall is maximized; leading to the highest F1 score, which in this case is 0.97. Overall, the confidence threshold of 0.395 provides the best trade-off for maximizing the model's effectiveness in accurately identifying tumor cases while minimizing false positives and negatives. Table 3 presents a comparative analysis of our model with other state of the art algorithms, considering accuracy.

Table 3: Comparative analysis

Author	Technique	Accuracy (%)
Althobaiti et al. (2022)	CFFNN	98.08
Udriștoiu et al. (2021)	CNN + LSTM	98.26
Rustam et al. (2021)	Logistic Regression (LR) and Random Forest (RF)	LR: 96.48, RF: 99.38
Sehmi et al. (2022)	DenseNet	95.61
Sanoob et al. (2016)	Neural Network	95.2
Xuan and You (2020)	RNN	95.1
Yao et al. (2021)	ConvLSTM	95
Liu et al. (2020)	CNN	92
Sarfaraz et al. (2019)	MLT	91.26
Hussein et al. (2019)	MTL	91.26
Ramya et al. (2021)	P-NN	90
Keyi et al. (2022)	Random Survival Forest	90
Keyi et al. (2022)	Random Survival Forest	90
Our model	ResNet + RPN	97

From the Table 3, our model was compared with other state of the art algorithms and it was observed that while our model competes among the best, it is most reliable due to its ability to correctly classify dynamic CT images of PC.

5. CONCLUSION

The system developed in this study provides an efficient and accurate method for detecting pancreatic cancer using CNNs with ResNet and RPN. The integration of the background class alongside tumor and no tumor classes proved beneficial in enhancing the model's reliability. Key metrics, including F1-score of 0.97, precision of 0.96562, and recall of 0.98944, demonstrate the effectiveness of the model in accurately classifying tumor regions while minimizing errors. Overall, this study demonstrates the feasibility of using deep learning techniques, particularly CNNs with ResNet and RPN, for improving the accuracy of pancreatic cancer diagnosis in medical imaging. The system's strong performance highlights its potential for assisting in early cancer detection, a critical factor in improving patient outcomes.

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