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ADVANCE DEEP LEARNING MODEL FOR DIGITAL SEGMENTATION OF PANCREATIC CANCER

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Abstract

Pancreatic Cancer (PC) is among the deadliest forms of cancer, with a high mortality rate due to its often-late diagnosis. Early detection plays a critical role in improving survival rates, but this remains a challenge in medical imaging. This study presents an integrated deep learning-based approach for the automated tracking and detection of pancreatic tumors using a combination of Convolutional Neural Networks (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 research methods involve data collection from Madely repository considering 201 patients of undergoing first-line surgery for Pancreatic Ductal Adenocarcinoma (PDA), across 25-75 years of age, and considering diverse stages of PC. 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. The results highlight the potential of deep learning models in medical diagnostics, particularly in addressing the complex challenge of early pancreatic tumor detection. The model was integrated as software and tested with real world PC CT image data. The results showed that our model was able to correctly classify the PC image and segment the infected region with 97% accuracy.

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

1. INTRODUCTION

In recent years, there has been a significant increase in the number of individuals diagnosed with pancreatic cancer worldwide (Hameed and Krishnan, 2022). Research conducted by Sarfaraz et al. (2020) has reported an average annual mortality rate of 1712 per 100,000 patients affected by this disease. Gordon-Dseagu et al. (2018) and Hu et al. (2020) listed some of the causes of the problem as high intake of alcohol consumption, aging, smoking, obesity, air and water pollution, hereditary factors, chronic pancreatitis, etc. Most recently, the application of medical imaging for the tracking, staging, and prognosis of PC has evolved to the forefront of the detection method (Hameed and Krishnan, 2022), utilizing radiological image acquisition methods such as Computer Thermograph (CT), Magnetic Resonance Imaging (CT), ultrasound, etc., However, Liu et al. (2019) posited that the distinction of a cancerous lesion from other pancreatic disorders, such as pancreatitis, a chronic inflammation of the pancreas, remains a major roadblock in the accurate and early diagnosis of PC. In addition, Kang et al. (2021) revealed that over 80% of PC

misdiagnosis was due to difficulty in sporting underlying cancer. To this end, the innovation of a reliable image qualitative characterization system to facilitate the quality of PC diagnosis remained a research hotspot (Althobaiti et al., 2022).

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).For example, Xin and Wang (2019) compared various ML algorithms such as SVM, KNN, and Convolutional Neural Network (CNN) to determine the best for the classification of PC. The study reported that CNN achieved the best performance when compared with the others. Similarly, Jonathan (2022) compared ML algorithms considering LR, SVM, ANN, and DT. The result showed that the ANN achieved better performance, while the SVM was the least. Kumar and Kumar (2021) used the bat algorithm for the optimization of ANN and then train it to classify PC. The result after training and testing reported the Bat-ANN superiority over the standalone ANN. From these studies, it was observed that the application of ANN has dominated the study for PC classification due to better performance against other ML algorithms.

To this end, studies like Watson et al. (2018) used Particle Swarm Optimization (PSO) to improve CNN classification. The PSO was used to improve parameters search of CNN and the result showed that classification error was minimized; however, due to the non-convex nature of CNN, the optimization algorithms suffer issues of pre-mature multiple local maxima and issues of convergence delay. Tuncer et al. (2019) used perceptual harsh function to optimize the classification accuracy of CNN and achieved 98.2% success. However, Althobaiti et al. (2020) argued that the complex anatomy of PC attributed to poor grey values of radiological images, large variation of size, volume, and texture of PC tissues will make it difficult to replica similar success in practice; hence there is need for better feature extraction approach to improve training performance of the CNN. 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). Hence, this study proposed a strategic feature extraction approach to optimize the performance of CNN training for the tracking and detection of PC.

2. THE PROPOSED SYSTEM DEEP LEARNING PC DETECTION SYSTEM

The proposed system applied for the tracking and detection of PC will be developed using major techniques such as data collection, convolutional neural network optimized with Hierarchical Spatial Pooling (HSP), and a pre-trained model. The block diagram of the proposed deep learning extractor is presented in Figure 1.The proposed HSP applied three filters of 55, 99 and 1313 to perform convolutional scan on the image feature maps at diverse spatial resolutions. Each filter captures different features within the input image. The spatial pooling operation then applied maximum pooling technique to reduce the spatial dimensions while retaining the most salient information. The deep extractor block diagram is presented in Figure 1.

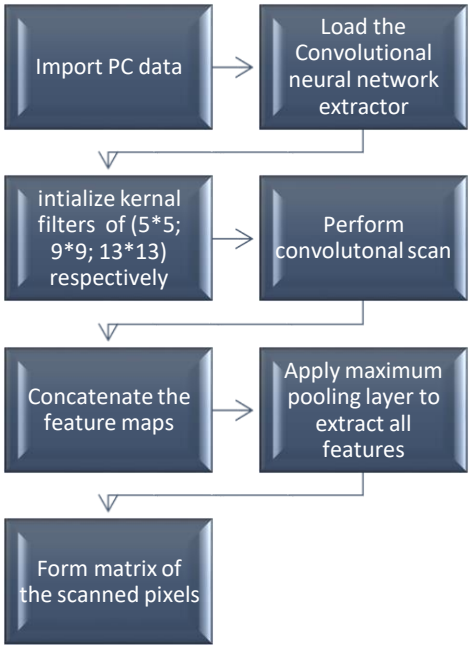

Figure 1: Block diagram of the Proposed Hierarchical Spatial Pooling (HSP)

The Figure 1 illustrates the proposed HSP model which used three convolutional filter to address issues of spatial information loss. The input CT images are scanned with each of the filters an then the feature maps identified are pooled using maximum pooling technique. Collectively the feature maps gathered from the three filters are concatenated and the used for form the next convolutional layer. This process was used to

optimize the feature extraction process and then generate maps which are applied to train ResNet and generate mode for the tracking and detection of PC. The Figure 2 presents the flow of the pancreatic cancer tracking and detection model.

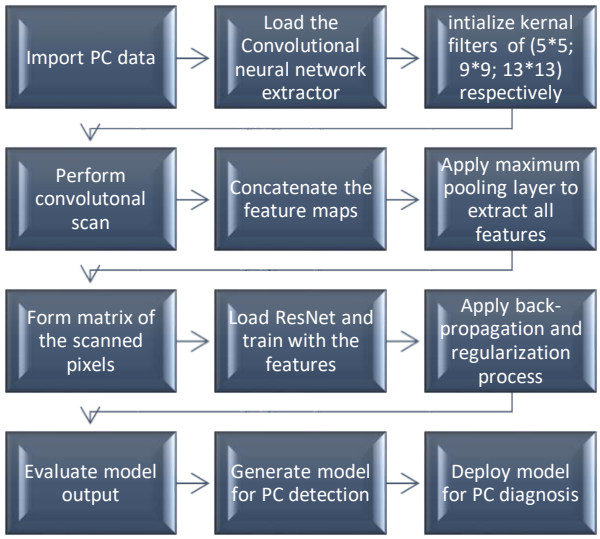

Figure 2: Block diagram of the Pancreatic cancer tracking and detection model

The Figure 2 presented a block diagram illustration of the proposed system. The data collected which considers diverse stages of PC was loaded into a data processing techniques for normalization and then feed to CNN architecture which has three convolutional layer, a fully connected layer were all the concatenated feature vectors are fashioned and then feed to the ResNet for training and model generation. The convolutional layer of the CNN was designed using three convolutional filters which performance a Heirarchical Spatial Pooling (HSP) process through convolutional scan and then concatenates the extracted feature maps. The ResNet which received the final extracted feature vectors concatenated are trained using back-propagation, regularization based dropout and performance evaluation until the best version of the model is generated for the classification of the PC. The architectural illustration of the deep learning based model for PC tracking and classification is presented in Figure 3;

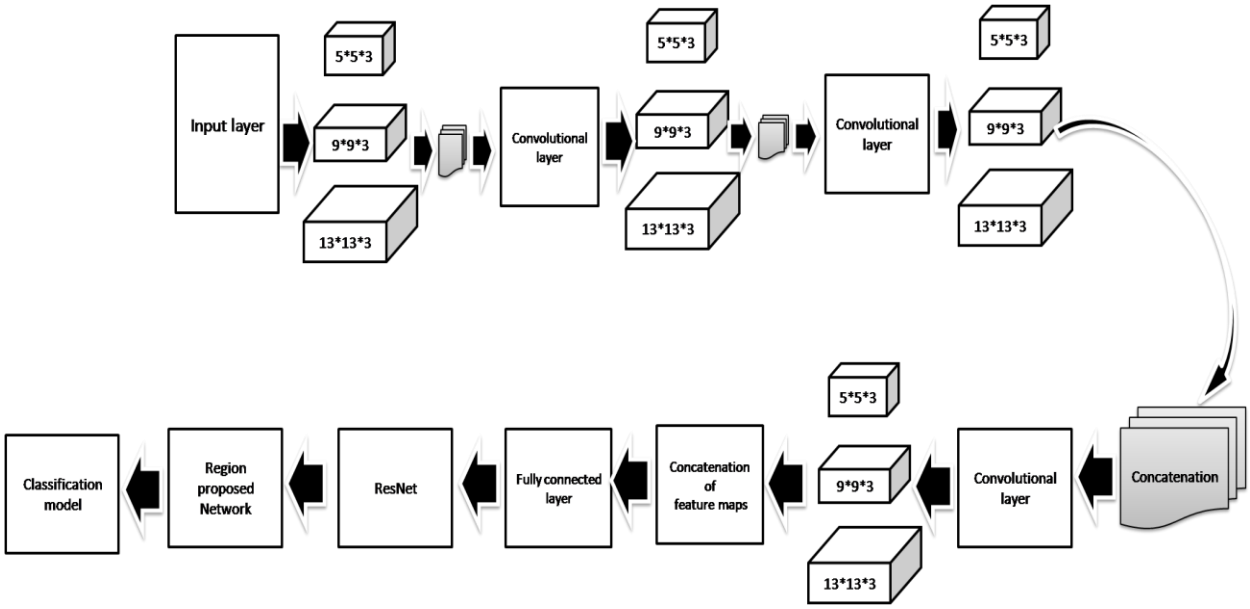

Figure 3: Architectural of the proposed deep learning PC tracking and classification

The Figure 3 showcased the architecture of the proposed PC classification model with deep learning. The processed input CT to the CNN was first extracted using the multiple filters in the HSP. This applied multiple filter sizes of (height weight color channel (3)) for the convolutional scanning of the image receptive fields and then concatenate the feature maps to form the next convolutional layer. This process continued until the final convolutional layer where the features are attended and feed to the fully connected layer which fusion the feature maps for training ResNet using optimization back-propagation and then generation of the classification model.

a. **Data collection**

The data collection for this study was from Madeley online data 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 are 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 57CT of 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.

b. 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 a 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 center of this range. This facilitates feature comparison between different images and enhances the interpretability of the CT data for feature extraction.

3. PROPOSED SYSTEM ALGORITHMS

The algorithm section outlines the core processes involved in the pancreatic cancer classification system. It details the sequential steps taken to input data, extract features, classify regions of interest, and generate output results. The algorithms employed in this system include the CNN extractor for feature extraction, the integration of ResNet with the Region Proposal Network (RPN) for identifying relevant image areas, and the overall integrated system algorithm that combines these components. Below are the specific algorithms used in the system.

3.1 CNN Extractor Algorithm

The CNN (Convolutional Neural Network) extractor algorithm is responsible for feature extraction from medical images. The steps involved are as follows:

1. ***Start***
2. ***Load the input medical image.***
3. ***Resize the image to the required dimensions (224x224 pixels).***
4. ***Normalize pixel values %% scale[0, 1]***
5. ***Convolutional Layers***
6. ***Set filter sizes [33; 55; 99], [11; 33; 99], [33; 55; 1313]***
7. ***Perform sequential parallel convolutional scan***
8. ***Pass the preprocessed image through a series of convolutional layers.***
9. ***Apply activation function for nonlinearity***
10. ***Apply multi-scale pooling layers***
11. ***Feature Map Generation***
12. ***Output Feature Representation***
13. ***End***

3.2 ResNet + Region Proposal Network (RPN) Algorithm

The combination of ResNet and RPN enhances the capability to identify and classify regions of interest in medical images. The algorithm operates as follows:

1) ***Start***
2) ***Feature Extraction input from CNN***
3) ***Utilize a pre-trained ResNet model to process the input feature maps***
4) ***Apply residual connections***
5) ***Initialize region proposal network***
6) ***Generate anchors of different sizes and aspect ratios across the feature maps.***
7) ***For each anchor, predict the probability***
8) ***Refine the anchor's coordinates.***
9) ***Filter proposals based on the confidence scores***
10) ***Region of Interest (ROI) pooling to extract features***
11) ***End***

3.3 Integrated System Algorithm

The integrated system algorithm combines the previous components into a cohesive workflow for the pancreatic cancer classification process:

1. ***Start***
2. ***Receive the medical image and associated patient data.***
3. ***Pre-process the image as described in the CNN extractor algorithm.***
4. ***Pass the pre-processed image through the CNN extractor to generate feature maps.***
5. ***Feed the feature maps into the ResNet model for deeper feature extraction.***
6. ***Apply the RPN to identify potential regions of interest (ROIs) within the feature maps.***

7. ***Filter and select the best proposals for classification.***
8. ***For each ROI***
9. ***Apply classification model to make predict***
10. ***Calculate the associated probability score***
11. ***Return results***
12. ***End***

3.4 Proposed System Flowchart

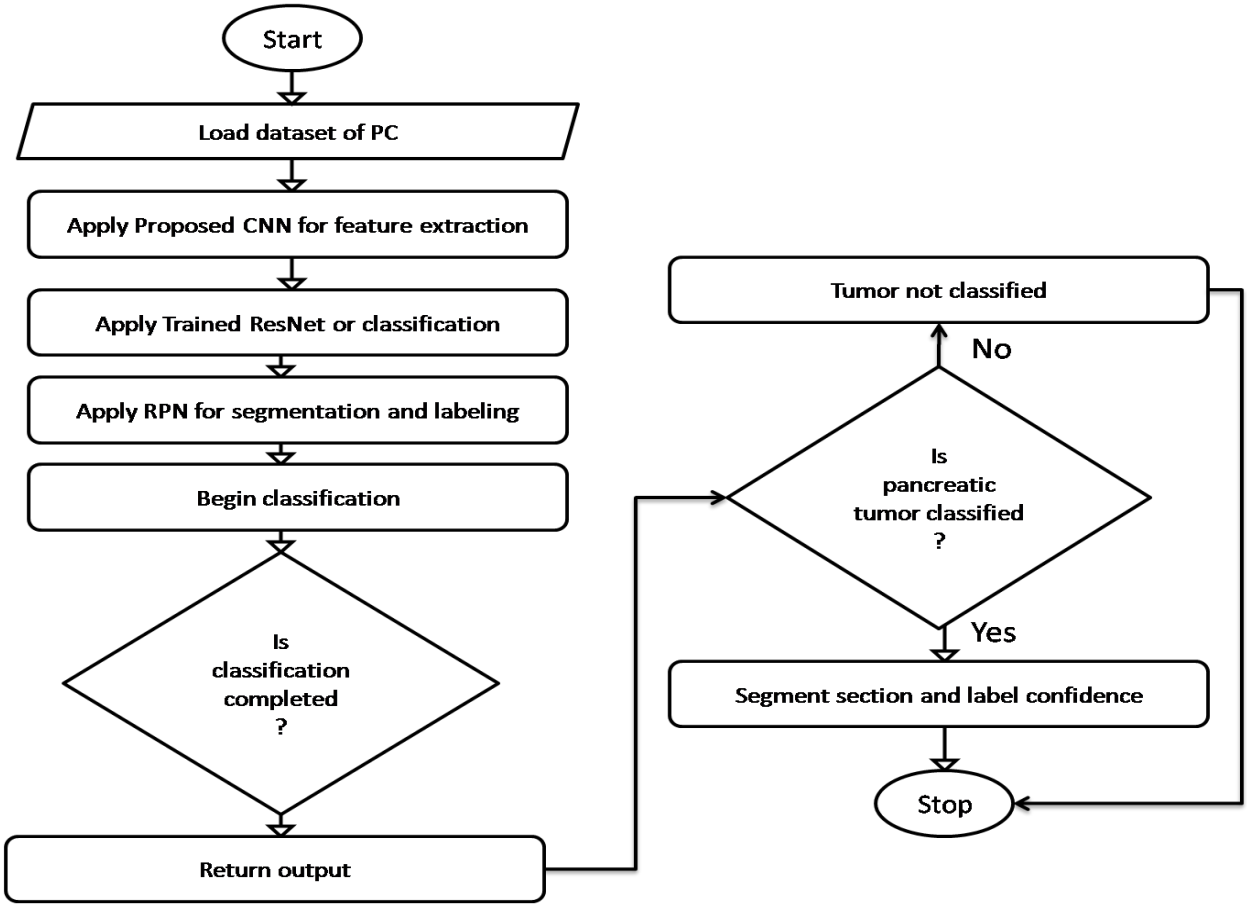

Figure 4: System flow chart for the PC classification system

The Figure 4demonstrated the low chart of the system operation. The data of PC upon loaded I to the system are extracted with the proposed CNN extractor which used multi scale filters to extract meaningful information from the CT data and feed to the trained ResNet classifier which classified the image and then segments the infected section with RPN upon classification as PC infected.

4. 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. Appendix B presents the source codes.

4.1 Hardware Requirements

Component	Specification	Description
Processor	Intel i5	A multi-core processor to handle image processing and computations.
RAM	16 GB	Sufficient memory to support data processing and model training.
Storage	1 TB SSD	High-speed storage for quick data retrieval and storage of images and models.
Graphics Card	NVIDIA GTX 1060	A dedicated GPU to accelerate deep learning model training and inference.
Display	1920 x 1080 resolution	A monitor with high resolution for better visualization of images and results.
Network	Broadband Internet Connection	For downloading datasets, software updates, and possibly cloud storage.

4.2 Software Requirements

Component	Version/Specification	Description
Operating System	Windows 10/11	A compatible operating system to run the application.
Python	Version 3.8	The primary programming language for developing the system.
TensorFlow	Version 2.0	For building and training deep learning models.
Keras	Integrated with TensorFlow	High-level API for building neural networks.
OpenCV	Version 4.0	For image processing tasks.
Pandas	Version 1.0	For data manipulation and analysis.
Matplotlib/ Seaborn	Latest version	For data visualization and reporting purposes.
Database Management System	MySQL, SQLite	For managing patient data and classification results.

5. SYSTEM TESTING AND RESULTS

System testing is a crucial phase in the development of the pancreatic cancer classification system, aimed at ensuring the system operates as intended and meets the specified requirements. This phase involves creating a structured test plan, utilizing appropriate test data, and comparing actual test results against expected outcomes. The thoroughness of this testing process is essential for validating the reliability and accuracy of the classification system in a clinical setting.

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.

This loss function measures how well the predicted bounding boxes for cancerous regions match the ground truth. Over the ten epochs, the training box loss shows steady improvement, starting at 1.3002 in epoch 1 and dropping to 0.67191 in epoch 10, indicating that the model is learning to localize cancerous regions more accurately. The validation box loss follows a similar trend, reducing from 1.7121 to 0.55188 over the same period, confirming that the model generalizes well to unseen data and maintains consistent localization performance across both training and validation sets.

This loss measures the accuracy of the model's classification of regions as benign or malignant. The training classification loss decreases significantly from

2.1621 in epoch 1 to 0.36031 by epoch 10, demonstrating that the model is progressively improving its ability to differentiate between the two classes. Correspondingly, the validation classification loss also shows significant improvement, reducing from 3.9586 in epoch 1 to 0.32721 in epoch 10. The consistent reduction in both training and validation classification losses indicates that the model is not overfitting and is performing well on unseen validation data.

The DFL loss focuses on refining the accuracy of the predicted bounding box coordinates. The training DFL loss decreases from 1.3797 in epoch 1 to 0.95063 in epoch 10, indicating the model is progressively improving its precision in defining the cancerous regions. The validation DFL loss also improves, decreasing from 1.7958 to 0.92047, suggesting that the model is consistently learning better localization strategies across different datasets.

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.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.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

The figure 5 presents the testing result of the ResNet + RPN using a real data of PC scan.

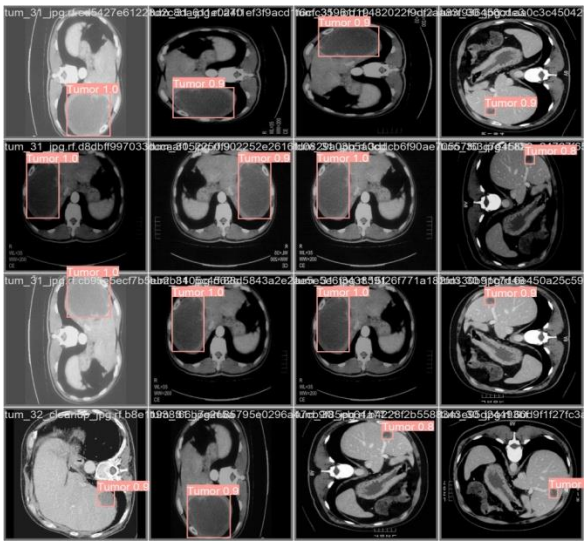

Figure 5: Classification result of the proposed deep learning model

The figure 5 presents the classification performance of our model using real data of PC collected from the testing set. The results showed that our model was able to correctly classify the segment of PC with tumor. The classification was done with ResNet, while the segmentation was done with RPN. The figure 6 presents the results of the system integration, while figure 7 and 8 reported the results of the testing with PC image A and Image B.

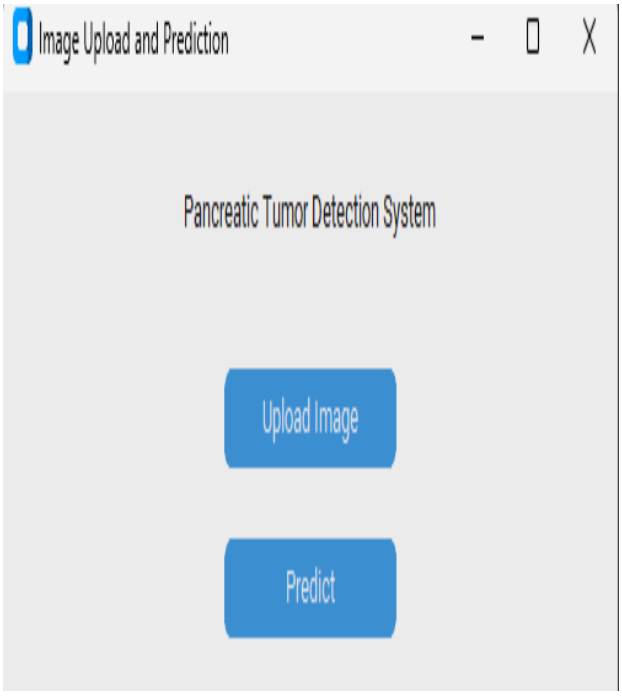

Figure 7: Result of the system implementation as software

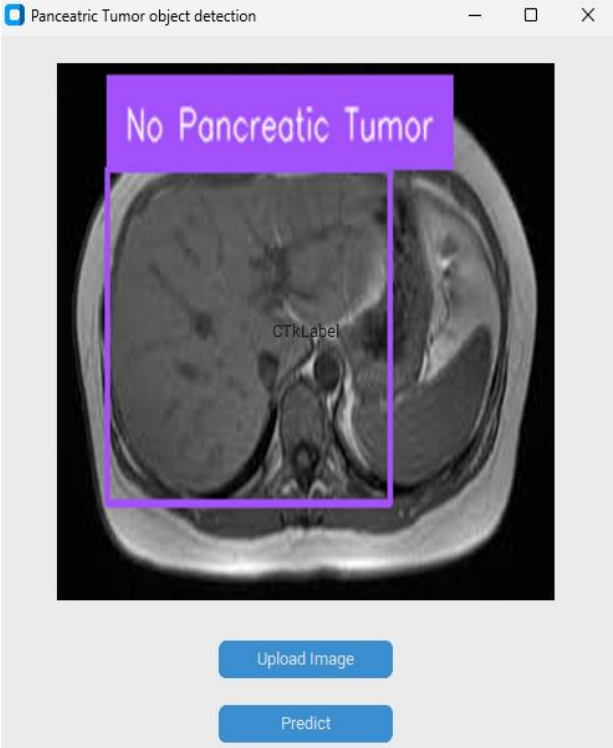

Figure 8: Experimental testing of the model with PC test image A

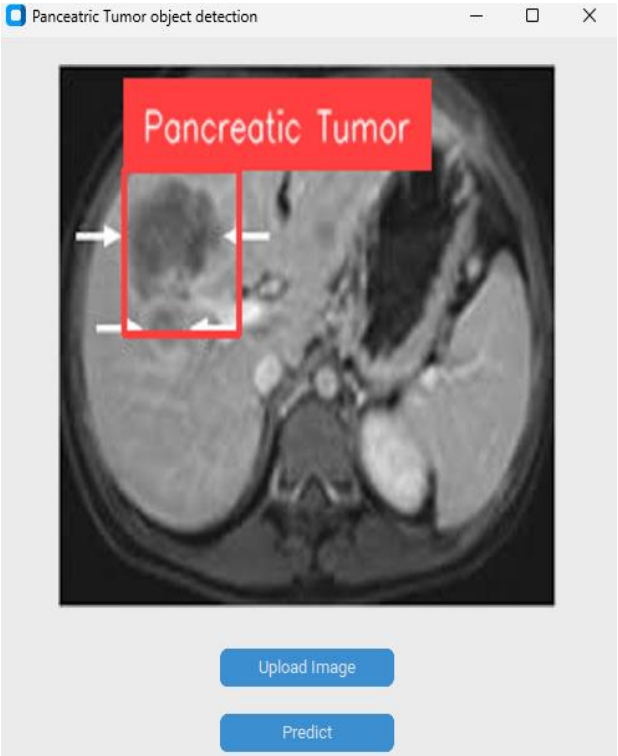

Figure 9: Experimental testing of the model with PC test image B

Figure 7 presents the interface of the software for the evaluation of the PC, while Figures 8 and 9 reported different classification outcome which showed that our model was able to correctly classify images with PC, and also the RPN segmented the section infected with the disease.

6. CONCLUSION

This research focused on developing a deep learning-based system for detecting pancreatic cancer using a combination of Convolutional Neural Networks (CNNs) with ResNet feature extractors and Region Proposal Networks (RPN). The primary goal was to enhance early detection accuracy by automatically identifying cancerous and non-cancerous regions in CT scans. The CNN architecture, utilizing ResNet as the feature extractor, enabled effective processing of complex medical images, while the RPN efficiently identified regions of interest (ROIs) for tumor detection.

During the training process, the model was trained on a dataset containing three classes: tumor, no tumor, and background. These classes allowed the model to not only distinguish between cancerous and non-cancerous regions but also to filter out irrelevant areas in the scans. Key metrics such as precision, recall, F1-score, and mean average precision (mAP) were used to evaluate the model's performance. The F1-score for all classes reached an optimal value of 0.97 at a confidence threshold of 0.395, indicating a strong balance between precision and recall. - The precision increased from 0.40135 in the early training epochs to 0.96562 by the final epoch, demonstrating consistent improvements in the model's ability to accurately classify tumors. Recall was also robust, reaching a maximum value of 0.98944, ensuring that the model effectively identified most of the cancerous regions, reducing the chance of missed diagnoses. - The mean average precision (mAP) for mAP50-95, which accounts for different IoU thresholds, improved from 0.1973 in the first epoch to 0.85331 by the last epoch, confirming the model's increasing proficiency in identifying correct tumor regions across different confidence levels.

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