RSNT-CHNN: A Novel Deep Learning Framework for Pancreatic Cancer Detection and Classification on CT Images Using Transfer Learning

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ABSTRACT

Pancreatic cancer remains one of the most dangerous cancers worldwide due to its aggressive progression, late-stage diagnosis, and limited detectability of early pathological changes in Computed Tomography (CT) imaging. Therefore, it is essential to provide early and accurate diagnoses with CT scans to enable timely medical interventions and improve survival rates. This study presents a novel stage-by-stage deep learning framework for the detection and classification of pancreatic cancer based on CT images, using a ResNet50-based Convolutional Hopfield Neural Network (RSNT-CHNN) to increase both diagnostic precision and reliability. The first step involves preprocessing to enhance image quality and eliminate any distortion present in CT images. Noise removal is achieved through a Wiener filter, which preserves structural data while removing noise in an efficient manner. The next step applies Contrast-Limited Adaptive Histogram Equalization (CLAHE) to increase contrast within the pancreas and highlight subtle differences between normal and abnormal tissues. In the segmentation step, a TransUNet-based segmentation model extracts the pancreas region from the CT images, effectively capturing the complex spatial features of the images and providing a more precise localization of the areas where possible cancerous regions exist. After segmentation, a deep feature extraction step is conducted via the ResNet50 architecture, which extracts robust hierarchical features from the CT images of the pancreas. These deep features are then input into the CHNN classifier, which uses convolutional learning and associative memory to accurately classify pancreatic cancer stages. Experimental results show that the proposed RSNT-CHNN framework reaches a classification accuracy of 98.10%, surpassing other state-of-the-art deep learning models. The results also demonstrate that combining advanced preprocessing techniques, a transformer-based segmentation model, deep residual feature extraction, and a Hopfield-based classification model can result in significant enhancements in the detection of pancreatic cancer. The proposed framework can be used as a highly effective computer-aided diagnostic tool to assist radiologists in the early detection and stage-wise classification of pancreatic cancer based on CT imaging.

Keywords-pancreatic cancer detection; stage-wise classification; Computed Tomography (CT); deep learning; TransUNet segmentation

I. INTRODUCTION

Pancreatic cancer is a significant global health problem due to its high mortality and poor prognosis. It is recognized as one of the most aggressive cancers with low five-year survival rates compared to other types of cancer [1]. The most common form of pancreatic cancer is Pancreatic Ductal Adenocarcinoma (PDAC), accounting for approximately 90% of all cases. Early detection of pancreatic cancer stages is critical in increasing patient survival rates and improving treatment outcomes. Pancreatic cancer progresses through multiple stages, starting from subtle cellular changes that gradually develop into premalignant lesions and localized tumors that ultimately become invasive cancer. In the early stages, morphological

changes within pancreatic tissues are difficult to identify. As the disease advances, tumors may increase in size and invade surrounding tissue or spread to distant organs. Accurately identifying each stage is important because treatment options—including surgery, chemotherapy, and radiotherapy—are highly dependent on disease stage [2]. Developing an automated system to classify pancreatic cancer stages would improve diagnostic accuracy and allow clinicians to implement timely intervention.

Computed Tomography (CT) imaging plays a major role in diagnosing and monitoring pancreatic cancer. CT provides radiologists with detailed images of abdominal organs and allows them to evaluate tumor size, vascular involvement, and possible metastatic spread. Although CT offers many advantages over other imaging modalities, detecting pancreatic cancer using CT images remains challenging. This is mainly due to the complex anatomy of the pancreas and the subtle intensity variations observed between different stages of the disease. Therefore, small lesions or early abnormalities can be difficult to identify, and manual interpretation can result in inter-observer variability and diagnostic fatigue. These challenges highlight the need for intelligent Computer-Aided Diagnostic (CAD) systems to assist radiologists in achieving more consistent and accurate diagnoses [3].

Recent advances in Machine Learning (ML) and Deep Learning (DL) have significantly improved automated medical image analysis. Specifically, Convolutional Neural Networks (CNNs) have demonstrated their ability to learn hierarchical and discriminative features directly from medical imaging data, facilitating automated detection, segmentation, and classification of abnormalities without relying heavily on hand-crafted features. However, existing studies often focus on binary classification tasks, such as normal versus cancerous tissue, instead of performing a detailed stage-wise classification of pancreatic cancer progression. Another factor influencing the performance of DL models is the selection of optimal hyperparameters. Parameters such as learning rate, batch size, network depth, optimizer selection, and convolution kernel dimensions significantly influence model convergence and generalization capability. Improper hyperparameter configurations can lead to overfitting, underfitting, or unstable training, which can decrease classification performance. Therefore, effective hyperparameter optimization strategies are essential to building robust and reliable multistage pancreatic cancer detection frameworks.

Motivated by the clinical and technical challenges related to pancreatic cancer detection and classification, this study proposes an intelligent DL-based framework for automated stage-wise pancreatic cancer detection and classification using CT images. This study utilized CT images obtained from a Kaggle dataset to develop and test the proposed framework. The pancreatic cancer conditions were classified into four distinct stages: Healthy (Normal), Benign (early abnormality), Pre-Malignant, and Malignant. The proposed system integrates advanced preprocessing techniques, accurate pancreas segmentation, deep transfer learning-based feature extraction, and optimized classification methods to effectively distinguish between these stages. The proposed framework focuses on stage-wise classification to improve early detection, improve diagnostic precision, and provide a support tool for clinicians to make informed decisions regarding pancreatic cancer diagnosis and treatment.

Several studies have explored Artificial Intelligence (AI) techniques for the detection of pancreatic cancer using CT images. In [4], an automated DL system was presented for image segmentation and classification for pancreatic cancer. This system utilized the Enhanced UNet model to segment tumor regions from CT images, and used a modified version of the ResNext model to classify cancers into two stages—Benign or Malignant—achieving a classification accuracy of 99.85%. The study in [5] explored the application of ML to automatically detect pancreatic cancer utilizing CT images. The SVM technique achieved a precision 83.07%, while the CNN achieved a significantly higher accuracy of 90.01%. ALO-CNN-GRU [6] can be utilized to identify tumors in CT images of patients diagnosed with pancreatic cancer and classify them into Benign and malignant types with a high level of diagnostic accuracy (99.92%). In [7], the necessity of early detection of pancreatic cancer to increase survival rates was emphasized. However, the utilization of traditional imaging methods has been limited by the requirement for contrast agents. Researchers are utilizing AI-based approaches to enhance the detection and classification of pancreatic cancer. In [8], a CNN-based approach inspired by the VGG architecture was proposed for pancreatic cancer detection using CT images. The model employed multiple convolutional layers with ReLU activation and max-pooling, followed by fully connected layers for classification. Weighted binary cross-entropy was used to address class imbalance, along with learning rate adjustment and early stopping. The results demonstrated effective classification of cancerous and healthy pancreatic tissues with an accuracy of 86.70%, sensitivity of 91.20%, a precision of 88.50%, and an F1-score of 89.83%.

In [9], a hybrid DL model was presented for the classification of pancreatic cancer using CT and MRI images. Specifically, CNN-based feature extraction (ResNet and EfficientNet) was combined with ML (SVM and Random Forest) classifiers, demonstrating better generalizability than traditional DL models and achieving an accuracy of 95%. In [10], the application of automated methods for diagnosing PDAC utilizing medical imaging was examined. A hybrid model, combining VGG16 and XGBoost, achieved an accuracy of 0.97, indicating that it is possible to combine DL models with traditional classifiers to improve detection accuracy. The study in [11] focused on the improvement of early detection of pancreatic cancer by identifying the reasons and the difficulties in finding the radiological signs of early pancreatic cancer. A hybrid method combined a novel method of feature extraction, using the Quaternion Wavelet Transform (QWT), and enhancing representation using Squeeze-and-Excitation (SE) networks, along with an SVM Classifier. In [12], recent architectures were employed and combined, achieving a classification performance of over 98% with ETEPCC-MDTL using CT images. In [13], CNNs and advanced DL techniques were employed for the development of a comprehensive method for the automated detection of pancreatic cancer.

II. PROPOSED WORK

Figure 1 shows the steps of the proposed method. Initially, a Wiener filter is applied to remove noise from the CT images. Then CLAHE is applied to increase local contrast to reveal subtle differences in intensity associated with structural changes in the pancreas tissue. Next, the TransUNet-based segmentation process is applied to delineate the boundaries of the pancreas from the CT images and enable accurate localization of the affected area(s) while excluding other interfering backgrounds. Finally, a deep feature extraction process utilizing the ResNet50 model is applied to extract deep features from the processed images, which are fed into a Convolutional Hopfield Neural Network (CHNN) classifier to model complex relationships between the features and perform an accurate stage-wise classification of pancreatic cancer.

A. Wiener Filter-Based Noise Removal

Noise can deteriorate image quality and hide small structural changes in pancreatic tissue that could be indicative of early-stage pancreatic cancer. The proposed framework utilizes a Wiener filter-based noise reduction method as the first pre-processing task. The Wiener filter is an adaptive linear filtering method designed to reduce the Mean Squared Error (MSE) between the original noise-free image and the filtered output image. In contrast to standard smoothers, the Wiener filter adaptively modulates its smoothing characteristics based on the local statistical characteristics of the image (Figure 2).

$$\hat{f}(x,y) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}[g(x,y) - \mu] \quad (1)$$

where $\hat{f}(x,y)$ represents the restored pixel value, $g(x,y)$ denotes the observed noisy image, μ represents the local mean of the neighbourhood, σ^2 denotes the local variance of the image, and v^2 represents the noise variance. This equation enables adaptive filtering by adjusting the contribution of the noisy pixel based on local statistical characteristics. By employing this noise reduction technique, the CT images are effectively denoised while retaining key anatomical structure and boundary information.

B. CLAHE-Based Contrast Enhancement

Pancreatic CT scans typically have low contrast, since there is usually a limited range of intensities within normal pancreatic tissue and the abnormal Region Of Interest (ROI). Early-stage pancreatic cancer lesions can have subtle intensity variations that make it difficult to visually identify these areas as different from the surrounding tissues. As such, increasing the contrast of pancreatic CT scans is an important task to help increase the visual resolution of the images and provide better visibility into possible abnormal regions. To accomplish this goal, the proposed RSNT-CHNN framework applies CLAHE to increase the local contrast of the pancreas CT scans. Unlike traditional histogram equalization methods, which increase the global contrast of all areas of an image, CLAHE is a localized technique that divides each image into smaller areas (or tiles). Each area (or tile) is histogram-equalized separately. Thus, CLAHE allows for increased detail enhancement and visualization of subtle tissue variations in the pancreas that would otherwise be difficult to detect through global techniques.

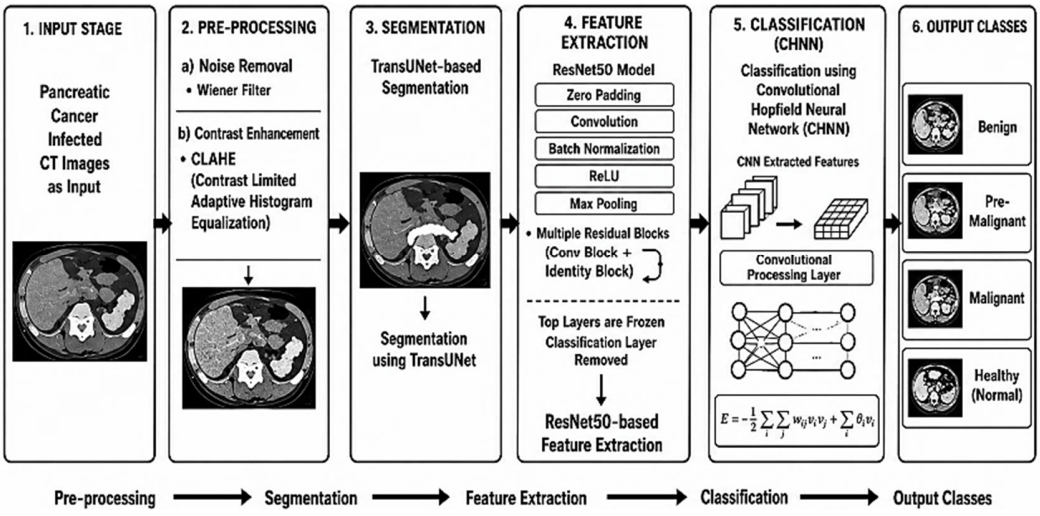

Fig. 1. Overall framework of the proposed RSNT-CHNN for stage-wise pancreatic disease detection and classification.

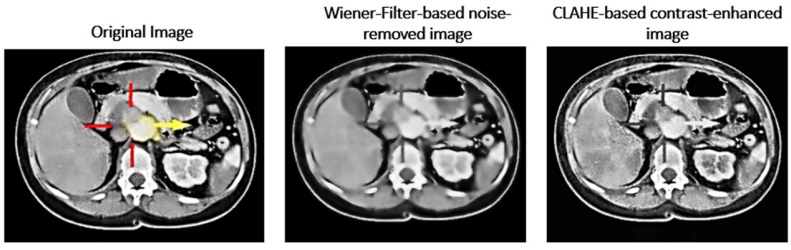

Fig. 2. Sample preprocessed pancreatic cancer CT image.

The CLAHE method also includes a contrast limiting mechanism that helps prevent excessive contrast enhancement caused by the presence of noise in the images. The pixel intensity transformations for CLAHE are based on the Cumulative Distribution Function [14] (CDF) of the local histograms. The transformed intensity is computed as

$$I_{out}(x,y) = \frac{CDF(I_{in}(x,y)) - CDF_{min}}{(M \times N) - CDF_{min}} \times (L-1) \qquad (2)$$

where $(I_{in}(x,y))$ represents the input pixel intensity at location (x,y), $I_{out}(x,y)$ represents the enhanced pixel intensity, CDF denotes the cumulative distribution function of the local histogram, CDF_{min} is the minimum non-zero value of the cumulative distribution function, $M \times N$ represents the number of pixels in the local tile region, and L denotes the number of possible gray levels in the image.

Applying CLAHE greatly improves the local contrast of pancreas CT scans, thereby enhancing the ability to visually resolve tissue structure and abnormal regions in relation to pancreatic cancer.

C. TransUNet-Based Segmentation

The pancreas is relatively small, located in proximity to numerous other abdominal organs; therefore, identifying the correct pancreatic region can be very difficult due to its anatomical complexity. An appropriate segmentation method is needed to accurately identify the pancreatic region and possible abnormal areas related to pancreatic cancer. This study employed the TransUNet segmentation method, a hybrid DL architecture that incorporates the strengths of both CNN and transformer-based self-attention mechanisms [15]. Although CNN architectures have proven successful at capturing local spatial features from images, the use of transformer-based self-attention mechanisms has demonstrated the ability to capture long-range dependencies and global contextual information. TransUNet follows a typical encoder-decoder architecture, similar to traditional UNet architectures. During the encoder phase, the convolutional layers extract low- and high-level feature representations from the input CT images. These feature representations are then transmitted to a Vision Transformer (ViT) module, which uses a self-attention mechanism to capture global contextual relationships between image patches. This ability of the ViT module allows the network to better understand the spatial relationships between different regions of the pancreas and surrounding tissues.

The segmentation process can be represented as $S = F_{TransUNet}(I)$, where I represents the preprocessed CT image, $F_{TransUNet}$ denotes the TransUNet segmentation function, and S represents the resulting segmented pancreatic region. By accurately separating the pancreas from irrelevant background, TransUNet significantly enhances the efficiency of subsequent processing stages. During the decoder phase, the extracted features are progressively upscaled and combined with the corresponding features obtained from the encoder phase via skip connections, allowing for precise localization and reconstruction of the segmented pancreatic region, as depicted in Figure 3. The segmentation output is generated as a binary or multi-class mask representing the pancreatic region within the CT image, as depicted in Figure 4.

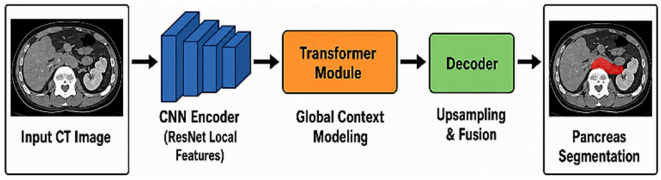

Fig. 3. TransUNet architecture used for segmentation.

Fig. 4. Sample segmentation output highlighting the pancreatic duct cancer region.

D. Feature Extraction Using ResNet50

Deep feature extraction has a significant effect on medical image analysis; it converts the raw, pixelated data of an image into high-level representations that can differentiate between various stages of disease. To obtain these high-level representations from the segmented pancreatic CT images, this study used a ResNet50-based CNN, employed as a transfer learning-based feature extractor with pre-trained ImageNet weights. Figure 5 shows ResNet50 as a pre-trained feature extractor, with the top classification layers removed and all convolutional layers frozen (the term 'frozen' indicates that the trained weights derived from large-scale datasets are preserved and not modified during training). This strategy significantly reduces the number of trainable parameters and computational complexity, while improving generalization performance and minimizing overfitting, particularly when training on relatively small-scale medical imaging datasets [16].

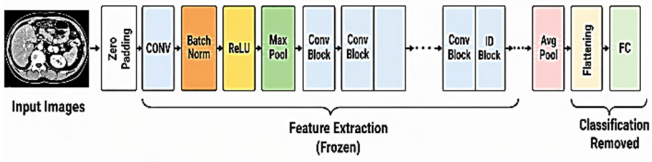

Fig. 5. ResNet50 architecture, used for feature extraction.

E. Classification Using CHNN

The proposed RSNT-CHNN system utilizes a CHNN, which integrates the ability of CNNs to learn features and the associative memory capabilities of Hopfield networks for performing robust multi-class classifications [17]. The CHNN has four major layers, as shown in Figure 6. Initially, the input feature layer receives the deep feature vector generated from the ResNet50 feature extraction module. These features provide the high-level semantic information related to pancreatic tissue structure and cancer patterns. Let the extracted feature vector be represented as shown below, where F denotes the input feature vector and f_n represents the n^{th} feature component.

$$F = [f_1, f_2, f_3, \dots, f_n]$$

Next, the feature vector is fed into the convolutional processing layer to apply convolution operations to find spatial correlation and enhance the discriminative feature patterns. The process of convolution is represented as

$$C_{i,j} = \sum_m \sum_n F(i-m, j-n) \cdot K(m,n) \quad (4)$$

where F represents the input feature map, K denotes the convolution kernel, and $C_{i,j}$ represents the resulting convolutional feature map at location (i,j). This layer refines the extracted features by emphasizing relevant spatial structures associated with pancreatic abnormalities.

After processing the above-mentioned convolution operation, the refined features are sent to the Hopfield associative memory layer, which is the core part of the CHNN model. Hopfield networks work according to the energy minimization principle. Energy minimization means that the Hopfield network continues to update the neuron states until a stable configuration, having minimum energy, is achieved. The energy function of the Hopfield network is described as

$$E = -\frac{1}{2}\sum_i \sum_j w_{ij}\, s_i s_j + \sum_i \theta_i\, s_i \quad (5)$$

where E represents the energy of the network, w_{ij} denotes the connection weight between neurons j, s_i, and s_j represent neuron states, and θ_i denotes the threshold value. The network seeks to minimize this energy function to reach a stable memory state corresponding to a specific class.

During the iterative update process, neuron states are updated according to:

$$s_i(t+1) = sgn(\sum_j w_{ij}\, s_i(t) - \theta_i) \quad (6)$$

where $s_i(t)$ represents the state of a neuron i at time t. The iterative updating continues until the network converges to a stable state.

Finally, the stabilized output representation is transferred to the classification output layer, which is used to assign the CT image to one of the pre-defined stages of pancreatic cancer. In this study, classification categories were Benign, Pre-malignant, Malignant, and Healthy (Normal).

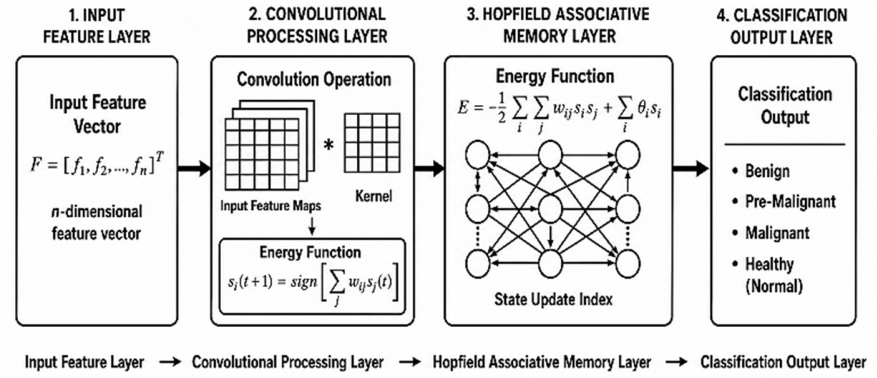

Fig. 6. CHNN architecture used for classification.

III. EXPERIMENTAL RESULTS

A. Implementation Setup

Experiments were conducted using a pancreatic CT image dataset, which consists of 26,400 images categorized into five types: Cancer Stage I–IV, and Non-Cancer [18]. For this study, four categories of interest were considered, which were labelled as Benign, Pre-Malignant, Malignant, and Normal. To address class imbalance, 2330 images were randomly selected from each class, resulting in a balanced dataset of 9,320 CT images, as presented in Table II. Figure 7 provides a visual representation of sample images, and Figure 8 presents the Training Accuracy (TACY), Testing Accuracy (TECY), Training Loss (TLOS), and Testing Loss (TELOS) of the RSNT-CHNN model through epochs.

TABLE I. ACTUAL DATASET DETAILS [18]

Class	Number of samples
Benign	5881
Pre-Malignant	5807
Malignant	5622
Healthy	2334
Total	**19,644**

TABLE II. BALANCED DATASET DESCRIPTION

Class	No. of samples
Benign	2,330
Pre-Malignant	2,330
Malignant	2,330
Healthy	2,330
Total	9,320

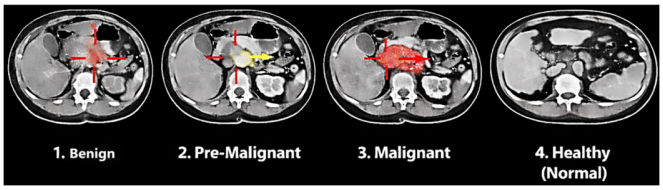

Fig. 7. Sample images

B. Discussion and Observations

The confusion matrices shown in Figure 9 demonstrate that the RSNT-CHNN model successfully classified the four categories (Healthy, Pre-Malignant, Benign, and Malignant) and had a very low misclassification rate. In order to create a

test set that is independent of the training set, the dataset was split into 70% training and 30% testing. Table III summarizes the quantitative results. During the testing phase, the average accuracy of the model was 98.30%, which clearly demonstrated that the RSNT-CHNN model has excellent discriminative capabilities. Additionally, the Precision-Recall and the Receiver Operating Characteristic (ROC) curves confirm the performance of RSNT-CHNN, showing that it performed at a very high level of both Precision and Recall and that the Area Under the Curve (AUC) was nearly equal to 1. These results show that the proposed method outperforms previous state-of-the-art models [20].

TABLE III. RESULTS OF THE PROPOSED RSNT-CHNN MODEL

Training phase (70%)					
Class	**Accuracy (%)**	**Precision (%)**	**Specificity (%)**	**Sensitivity (%)**	**F-score (%)**
Benign	98.10	97.90	98.30	97.80	97.85
Pre-Malignant	98.30	98.00	98.50	97.90	97.95
Malignant	98.20	97.80	98.40	97.70	97.75
Healthy	98.30	98.10	98.60	98.00	98.05
Average	98.23	97.95	98.45	97.85	97.90
Testing phase (30%)					
Class	**Accuracy (%)**	**Precision (%)**	**Specificity (%)**	**Sensitivity (%)**	**F-score (%)**
Benign	98.20	98.00	98.40	97.90	97.95
Pre-Malignant	98.40	98.10	98.60	98.00	98.05
Malignant	98.10	97.80	98.30	97.70	97.75
Healthy	98.50	98.20	98.70	98.10	98.15
Average	98.30	98.03	98.50	97.83	97.98

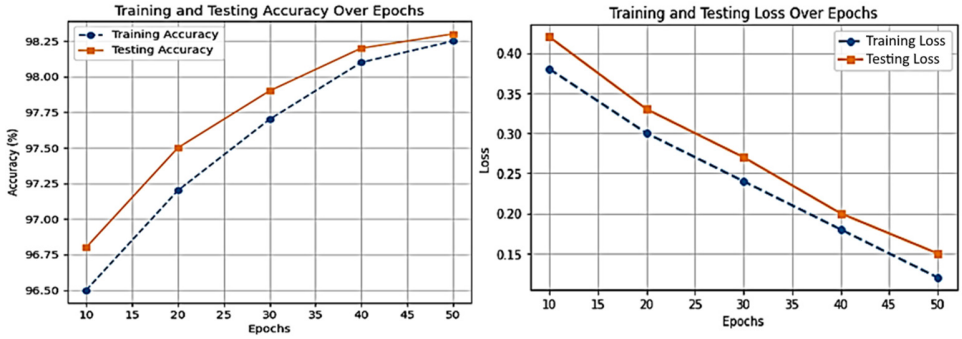

Fig. 8. Accuracy and loss graph of the proposed RSNT-CHNN model based on the training and testing sets.

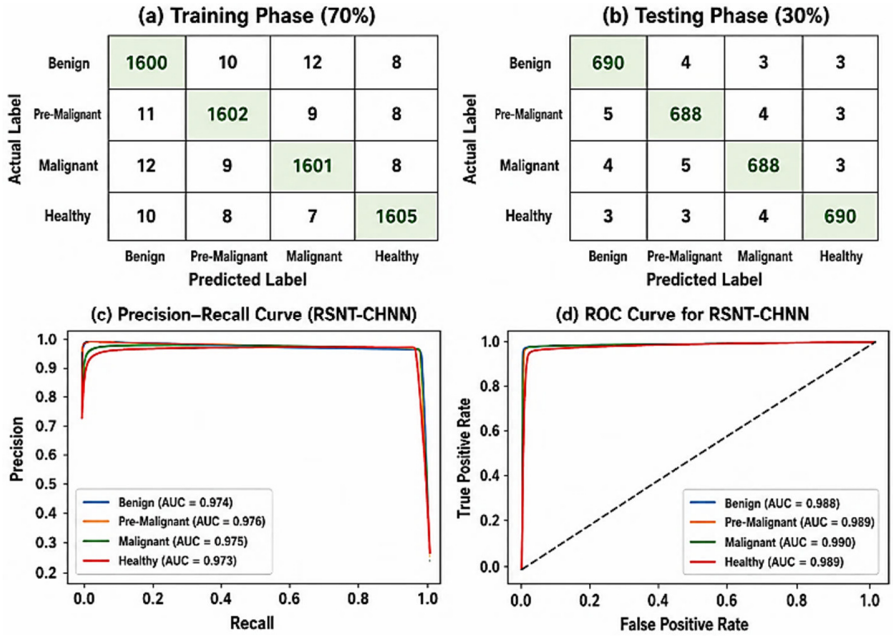

Fig. 9. (a, b): Confusion matrices based on the TR and TS sets; (c, d): Precision-Recall and ROC curves.

IV. CONCLUSION

This study presents an RSNT-CHNN-based system for automatically detecting and staging pancreatic cancer from CT images. The proposed framework uses a Wiener filter and CLAHE to effectively preprocess CT images, TransUNet to accurately segment the ROI, ResNet50 to extract deep features, and a CHNN to classify the ROI. By combining all these modules, the model captures both local and global context

information for better classification performance. Unlike existing pancreatic cancer detection models that rely mainly on conventional CNN-based classification, the RSNT-CHNN model integrates transformer-based segmentation, transfer learning-based deep feature extraction, and Hopfield associative memory classification within a unified architecture for accurate pancreatic disease classification. Experimental results show that the proposed RSNT-CHNN model outperforms other state-of-the-art deep learning architectures, achieving a high classification accuracy of 98.30% and high sensitivity, precision, and F-score values. The obtained results demonstrate that the integration of transfer learning and CHNN-based classification effectively improves feature representation and classification reliability for pancreatic cancer detection. The proposed framework exhibits strong generalization capability across different cancer stages, indicating its robustness for real-world clinical scenarios. The ability to accurately identify early-stage abnormalities highlights its potential to support timely diagnosis and improve patient outcomes. Thus, the proposed framework can serve as a supportive CAD tool for assisting clinicians in the detection of early-stage pancreatic cancer. Future work will focus on validating the model using larger multi-institutional datasets and improving its real-time clinical applicability.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work.

ACKNOWLEDGMENT

Not applicable to this work.

DATA AVAILABILITY

The dataset used in this study is publicly available at [18].

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