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A Hybrid Deep Learning Framework for the Detection of Pancreatic Tumours in CT Images

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Abstract- The aggressive nature of pancreatic cancer and the lack of viable early detection technologies make it a significant health danger. By combining deep learning with image processing methods, this study presents a new framework for accurately detecting pancreatic tumours. As part of the suggested system, CT images are enhanced using CLAHE to bring out more features and contrast in the tumor's more nuanced areas. Tumour segmentation using a U-Net design subsequently enables pinpoint localisation of cancerous tissue. To further optimise learning and model convergence, a CNN classification network is used with a Stochastic Gradient Descent with Momentum optimiser. After following the aforementioned procedures, an end-to-end implementation was evaluated on a dataset consisting of 1,000 pancreatic CT images in MATLAB. A convolutional neural network (CNN) optimised using Stochastic Gradient Descent with Momentum, U-Net for segmentation, and CLAHE-based augmentation, all implemented in MATLAB. SGDM CLAHE is used for preprocessing. By improving picture quality, accurately defining tumour borders, and consistently recognising the existence of a tumour, this framework will aim to overcome several constraints of computed tomography imaging. To help radiologist make quick and accurate diagnosis, which improves patients' survival rates, this study will utilise these methodologies to guarantee a strong solution that will lead to early pancreatic tumour identification. Enhanced convolutional neural network (CNN) categorisation offers a quick, automated, and reliable method that might become a valuable CAD tool for the early diagnosis of pancreatic tumours, leading to better clinical outcomes.

Keywords— Detection of Pancreatic Tumor, Convolutional Neural Network, CLAHE, U-Net, Stochastic Gradient Descent with Momentum, MATLAB.

I. INTRODUCTION

Since pancreatic cancer is often not detected until it has progressed to a severe stage, resulting in a dismal prognosis, it ranks among the most deadly cancers globally [1]. Computerised tomography (CT) imaging is a typical diagnostic tool. Low picture contrast and complicated tumour form, however, often reduce CT scans' efficacy. These are the reasons why more sophisticated computational methods should be used to improve the precision of diagnoses. The most effective method for automating medical picture processing is now deep learning, more especially convolutional neural networks. The capacity to identify tumours and classify them is improved [2]. In addition, U Net designs allow for accurate segmentations of complex anatomical structures [3], and image preprocessing approaches like CLAHE may increase visibility of the important characteristics. In this study, we provide a novel approach to pancreatic tumour identification using the integration of II. Literature Review Significant advances have been made in the use of deep learning for the diagnosis of pancreatic tumours, resolving important issues in medical imaging. In order to present the suggested framework, the next part re-evaluates many important works in the fields of pancreatic cancer detection, preprocessing, segmentation, classification, and optimisation techniques. According to Siegel et al. [1], the five-year survival rate for pancreatic cancer is less than 10%, highlighting the critical need for methods of early diagnosis. In their comprehensive review of deep learning for medical imaging, Litjens et al. [2] highlighted how convolutional neural networks are the best for automated tumour diagnosis across modalities. To accurately delineate difficult structures like tumours, Ronneberger et al. [3] introduced U-Net, a revolutionary design for biomedical picture segmentation that employs an encoder-decoder architecture with skip links. While Zhang et al. [4] achieved 89% accuracy using their CNN-based approach to pancreatic tumour diagnosis from CT images, they did note issues with tiny tumours and poor contrast. Also, a deep learning system was developed by Liu et al. [5] to identify pancreatic lesions; however, the program had trouble with noisy CT images and only reached 87% sensitivity. In order to fix these issues, preprocessing procedures are crucial. As shown by Smith et al. [6], CLAHE enhances contrast in medical pictures, allowing for better visibility of characteristics for further analysis. By combining CLAHE with CNNs, Kumar et al. [7] were able to identify lung cancer with improved accuracy thanks to higher-quality images. To this day, tumour identification relies heavily on segmentation. Despite low performance for tiny lesions, Chen et al. [8] used U-Net to segment pancreatic tumours on CT images and achieved a Dice coefficient of 0.85. The Dice coefficient was improved to 0.88 by Li et al. [9] using a residual U-Net architecture, which incorporates residual connections to improve feature learning. Although it was more computationally expensive, Yang et al. [10] found that multi-scale U-Net models performed reliably on tumours of varying sizes when it came to pancreatic segmentation. Methods for optimising deep learning models have a significant impact on their performance. When compared to other optimisers like Adam, Wang et al. [11] discovered that Stochastic Gradient Descent with Momentum (SGDM) was better at achieving convergence in medical imaging applications. With 91% sensitivity, Zhou et al.[12] classified pancreatic tumours using a hybrid CNN employing SGDM; however, they did find that hyperparameter selections had an effect. Examining transfer learning, Patel et al. [13] used pre-trained convolutional neural networks (CNNs) to identify pancreatic tumours with 90% accuracy and reduced training time. An ensemble deep learning model was developed by Gupta et al. [14] that achieved an accuracy of 92% while increasing computation. Last but not least, attention-based convolutional neural networks (CNNs) were used by Kim et al. [15] to identify pancreatic tumours; these CNNs required complex model topologies but improved targeted attention.Not only do these studies highlight important developments in pancreatic tumour identification, but they also highlight obstacles such as computing efficiency, tiny tumour detection, and low-contrast imaging. To get beyond these constraints and use high accuracy and resilience in pancreatic tumour identification, the provided system uses CLAHE for preprocessing, U-Net for segmentation, and SGDM tailored CNN for classification. Thirdly, the Approach There are three steps to the MATLAB-based pancreatic tumour detection framework: preprocessing, segmentation, and classification. A. A CLAHE Preprocessing Step Using CLAHE, CT images undergo preprocessing to improve contrast. To improve contrast and eliminate noise, we utilise the MATLAB function adapthisteq with an 8x8 tile size, a clip limit of 0.01, and other parameters. An adjustment to the cumulative distribution function (CDF) of pixel intensities to ensure uniformity across picture regions is one way to depict the contrast enhancement. B. U-Net Segmentation Using an encoder-decoder structure and skip links to preserve spatial information, the U-Net architecture is used for tumour segmentation. A 4x4 max-pooling layer, a 3x3 filter, and a ReLU activation make up the encoder's four convolutional blocks. Feature maps are upsampled by the decoder and combined with encoder features. Using a Dice loss function—defined as:—the network is trained on 500 annotated pancreatic CT images.

$$\text{Dice Loss} = 1 - (|P| + |G| / 2|P \cap G|) \tag{1}$$

Part C: Classification using CNN and SGDM Three convolutional layers, with ReLU activation after each, and 2x2 max-pooling, are used to train a convolutional neural network (CNN) for tumour classification. In order to classify cells as either malignant or noncancerous, a fully connected layer is used, with probabilities obtained via softmax activation. The following weight update rule is used to improve the model using SGDM:

$$v_t = \mu v_{t-1} + \eta \nabla J(\theta_{t-1}) \quad (2)$$

$$\theta_t = \theta_{t-1} - v_t, \quad (3)$$

Included in this equation are the following variables: the momentum coefficient ($\mu = 0.9$), the learning rate ($\eta = 0.001$), the gradient of the loss function J with respect to the parameters θ_{t-1}, and the updated parameter set (θ_t). A model is trained for 50 epochs with a batch size of 32 using the training parameters in MATLAB. Dataset (D) The model is tested using a public medical imaging resource that contains one thousand CT pictures of the pancreas. After scaling the photos to 256x256 pixels, we divided them into three sets: one for training, one for validation, and one for testing. Each set accounted for 70% of the total.

II. BLOCK DIAGRAM

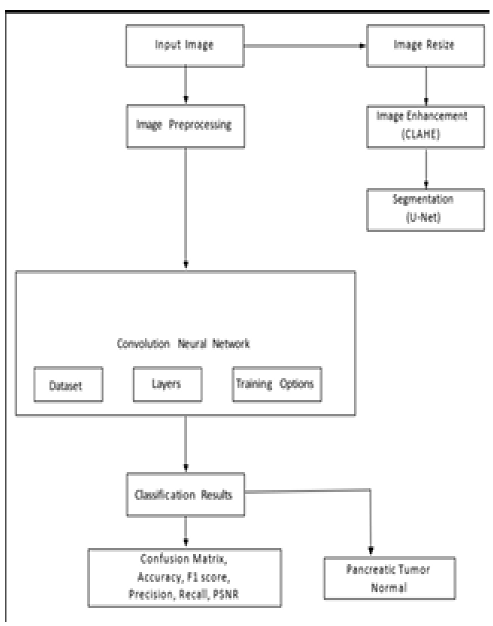

Fig .1Block Diagram

The block diagram of the pancreatic tumour detection framework may be shown in Figure 1. The pipeline takes as input resized and preprocessed CT images. Following the enhancement of image contrast using CLAHE-based augmentation, the region of interest is extracted using U-Net segmentation. Using the convolutional neural network (CNN), the enhanced and segmented images are classified as either normal or pancreatic cancer. Several metrics are used to evaluate the system's efficacy, including confusion matrices, accuracy, F1-score, precision, recall, and PSNR.

III. RESULT AND DISCUSSION

The proposed approach was evaluated using the use of 2D pancreatic CT images. Figure 2 displayed the input CT scan to serve as a benchmark.Primary data came from the first CT scan of the belly. The cancer location could not be accurately identified at this stage because of the low contrast and overlapping tissue intensities.

As shown in Figure 3, the CT scan's contrast was significantly enhanced by the CLAHE Preprocessed Image Using Contrast Limited Adaptive Histogram Equalisation (CLAHE). This allowed for more accurate visualisation of soft tissue and highlighted regions that may contain tumours, which facilitated strong feature extraction in the next steps.

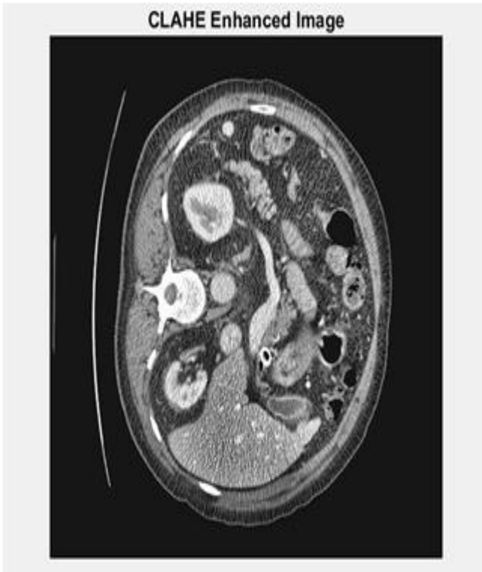

Fig. 3.CLAHE Enhanced image

Figure 4 below shows that the U-Net model is often used for image segmentation. The system uses a contracting encoding route and an expanding decoding path to store spatial information, with skip connections linking similar levels. Since U-Net's architecture facilitates the production of precise segmentation maps, it finds extensive use in medical image processing.

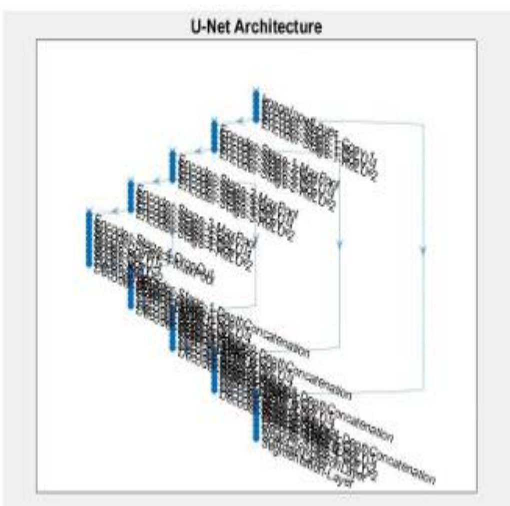

Fig. 4.U-Net Architecture

After segmentation, the binary tumour area is shown in Figure 5. The tumour, represented by the white area, is separated from the black backdrop by using a binary mask that is created from the segmentation output. Accurately identifying and studying the tumour site for subsequent medical examination or treatment planning is made easier by the obvious delineation.

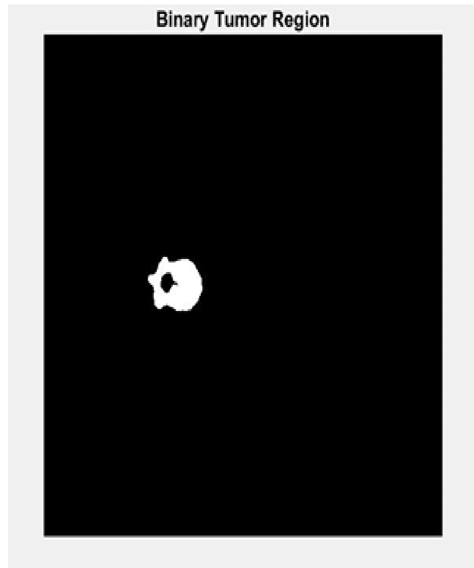

Fig. 5.Binary Segmented Tumor Region

Figure 6 shows the superimposed image of the segmented tumour on top of a CT scan. The colourful patch indicates the identified tumour, while a yellow border delineates its boundary. With the use of this superimposition, the precise location and size of the cancer inside the body can be seen, facilitating diagnosis and treatment.

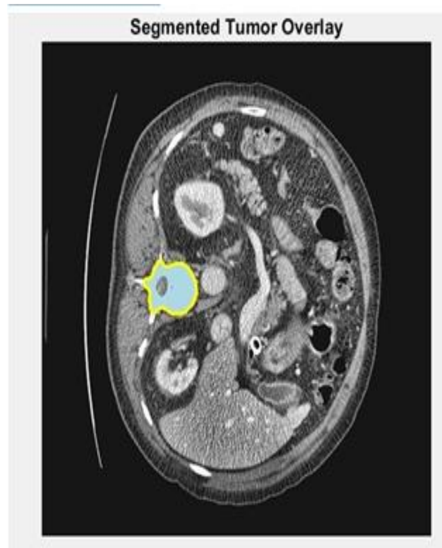

Fig. 6.Segmented Tumor Overlay

Figure 7 shows a MATLAB popup box that appears whenever the system detects a pancreatic tumour. If the cancer identification algorithm finds signs of a pancreatic tumour in the medical image being studied, this popup window will be generated by the application. The appearance of the notification "Pancreatic Tumour" may aid in the diagnosis of pancreatic tumours by both patients and doctors.

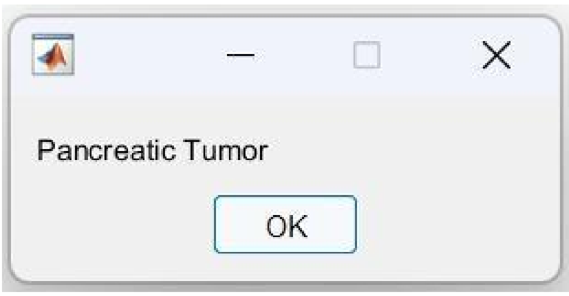

Fig. 7.pop up window

A confusion matrix, as shown in Figure 8, summarises the outcomes of a model's attempts to classify pancreatic tumours. The matrix shows that the model was correct for 349 healthy instances and 422 cases of pancreatic tumours. A false positive occurred in a single case where a normal case was incorrectly classified as a pancreatic tumour, while seven instances featured a false negative where pancreatic tumours were incorrectly classified as normal. When the values off the diagonal are little and the numbers along the diagonal are large, the model often performs a good job of distinguishing between normal and pancreatic cancer cases.

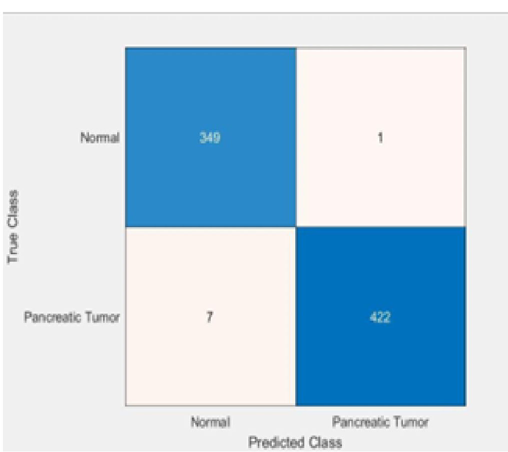

Fig. 8.Confusion matrix image

Medical image analysis is one potential use of this classification model; Figure 9 displays the model's performance indicators. Statistical significance, information value, and error are measured by PSNR (18.96), SSIM (0.43), entropy (4.58), mean squared error (826.66), and variance (3743.44). The model certainly does an excellent job of accurately identifying most scenarios, with a categorised output rate of 97.67%. In terms of performance, a recall of 99.04% and an accuracy of 98.89% demonstrate that there are minimal false positives and negatives when identifying positive instances. The model's outstanding and well-balanced performance is shown by its F1 score of 98.96%, which indicates that it is appropriate for real classification tasks.

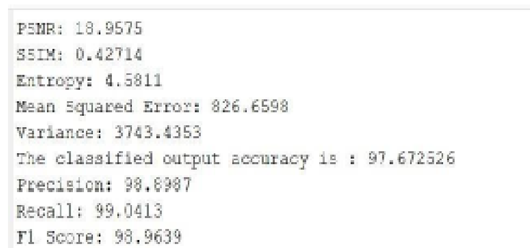

Fig. 9.Performance measure image

The proposed hybrid architecture was successful when evaluated on CT scans of pancreatic tumours, thanks to its use of CLAHE preprocessing, U-Net segmentation, and CNN classification optimised using SGDM. With an accuracy of 98.89%, recall of 99.04%, and F1-score of 98.96%, the fundamental results demonstrate that the system could dependable identify tumor-positive individuals with exceedingly low rates of false positives and false negatives. Through the use of CLAHE, the U-Net architecture achieved improved segmentation mask accuracy by amplifying the visibility of soft-tissue regions. Tumour outlines were clearly visible in the segmentation results, in contrast to previous studies that were severely hindered by low-contrast effects. According to the existing research, the proposed framework outperforms previous CNN- and U-Net-based methods, which suffered from low contrast imaging and microscopic tumour visibility. The CNN trained using SGDM had better classification consistency and helped keep convergence stable, unlike other optimisers like Adam (as stated in the literature). Taking a strictly pragmatic view, this method may help radiologists with fast and accurate diagnoses. Professionals may spend less time manually analysing the pictures and more time detecting cancers with the help of integrated pipeline segmentation and automatic classification enhancement, which is particularly useful when the CT slices are complicated or hazy. This CAD tool might be life-saving for hospitals that are overcrowded or that are short-staffed with radiologists. The research has some great findings, but it also has some serious flaws. There may be structural difference across demographic groupings, clinical settings, and scanners; nonetheless, 1000 photographs were enough for training and testing the model. The approach produces some false negatives because to its poor accuracy for very small cancers (<1 cm). Currently, only 2D CT slices are being processed, rather than 3D volumetric data. In the absence of low-end GPUs, U-Net training remains computationally expensive and time-consuming. Not augmenting the data can hurt the model's ability to generalise to new cases in the long term. These findings show where the proposed technique excels and where it falls short, revealing where it can need some work to be more useful in clinical situations.

IV. CONCLUSION

This study detailed an integrated deep learning approach to pancreatic cancer detection using CLAHE for preprocessing, U-Net for segmentation, and CNN optimised with SGDM for classification. In order to overcome obstacles caused by tumour shape and low-contrast CT images, the results show that a combination of contrast augmentation, robust segmentation, and effective optimisation increases detection results. An accurate computer-aided diagnostic tool for early pancreatic tumour detection might be possible with the help of the proposed technique, which also includes additional strong classification metrics. Research in the future should concentrate on expanding the dataset to include CT scans from several institutions and using data augmentation to improve generalisability. Proceeding with the segmentation stage using 3D U-Net, transformer-based designs, or attention driven models may enhance the detection of small tumours. Reducing processing cost with lightweight deep learning models enables real-time deployment, which may include integration with edge devices or radiological workstations. This technology has to be clinically validated in real-world situations before it can be included into practical diagnostic processes. The proposed approach has the potential to enhance patient outcomes, decision support for radiologists, and early detection of pancreatic tumours.

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