Image segmentation using Contextual Learning of Histopathology images of colon cancer

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***Abstract*— Early and automatic detection of colorectal tumors is crucial for the analysis of cancer. A novel strategy for segmenting histopathology images involves the application of a Contextual Learning Network auto-encoder (CENET). The architecture of CENET proposed integrates a convolutional neural network (CNN) with an encoder-decoder framework that incorporates mechanisms for capturing contextual information. The encoder is accountable for extracting categorized features from histopathology images, while the decoder generates segmentation masks by up sampling the features to match the original image resolution. By leveraging contextual learning techniques like multi-scale features and attention mechanisms, CENET achieves impressive segmentation outcomes. Assessment metrics such as mean Dice Similarity Coefficient (mDSC), mean Intersection over Union (mIoU), recall, and precision highlight the efficacy of CENET in precisely outlining regions of interest in histopathology images. Demonstrating a mean DSC of 0.904, mean IoU of 0.848, recall of 0.923, and precision of 0.907, the proposed CENET model exhibits commendable performance in segmenting histopathology images for applications in cancer diagnosis and treatment planning. The outcomes derived from segmentation act as features for further extraction and classification of both benign and malignant colon cancer.**

***Keywords*— Contextual Learning, Colon Cancer Classification, CE NET**

I. INTRODUCTION

Colorectal-Cancer is a significant cause of cancer-related deaths globally, requiring initial detection & treatment of polyps to preclude cancer spread. [1]is vital for identifying colon irregularities and eliminating premalignant polyps. Nevertheless, accurately segmenting polyps in colonoscopy images is challenging due to their varied appearance and unclear boundaries. The study explores augmentation techniques to improve polyp semantic division using the U-Net model. [2]The analysis indicates that the most actual technique is in the scenario with an input size of 320×320.

The morphology of glands is analysed by pathologists to assess the malignancy of adenocarcinomas, a common cancer type. Histopathology image analysis is crucial for accurate and scalable diagnosis[3], with gland segmentation being a key component. A method is proposed in this study to effectively separate gland instances. The segmentation process is treated as a multi-task learning problem, generating maps for gland objects, contours, and touching boundaries simultaneously. This methodology employs end-to-end learning and is applicable to a range of base networks. [4].

Accurate polyp segmentation is important for colon cancer diagnosis and treatment. Deep convolutional networks extract common high-level features, but may ignore individual features leading to fuzzy results. [5]a segmentation frame is proposed using deep and classification features. Batch norms maximization second-hand to enhance predict map.[6] A two classification mechanism categorizes prediction maps into simple and complex samples. Prediction maps of simple samples, resembling binary images, are not processed.

The research introduces a computerized Hybrid U-Net model designed for analysing morphometric characteristics of colon glands and providing information on cancer grade It integrates Advanced Convolutional Learning Modules, Attention Modules, and Multi-Scalar Transitional Modules into the U-Net framework. to enhance feature learning. Experiments involve CRAG, GlaS challenge, LC-25000 dataset, and Hospital Colon datasets, showing competitive results in gland detection and segmentation tasks. Pathologists evaluated the model's performance in determining cancer grade, with high precision, specificity, and sensitivity. Gradient-Weighted Class Activation Mappings emphasize key regions for cancer prediction, assisting pathologists in diagnosis. The results will assist pathologists in histopathology images asses.

Medical image segmentation is crucial for healthcare, especially in surgery planning. Transanal total mesorectal excision (TaTME) is important in treating colon and rectum cancers. [8]Real-time instance segmentation during TaTME can assist surgeons and reduce risks. Precise segmentation of TaTME images is complex due to anatomical variations. Deep learning is effective in medical image segmentation but struggles with complexity in TaTME data. A lightweight dynamic convolution Network (LDCNet) is proposed to address this issue.[8] .

LDCNet shows superior segmentation performance compared to existing models. The code for LDCNet is available. spent, reducing errors and speeding up cancer detection.

II. LITERATURE SURVEY

Colorectal cancer ranks as the third maximum frequent cancer type in the United States, as documented by the Centers for Disease Control and Prevention (CDC). Males exhibit elevated rates of colon-cancer compared to females. Individuals of Black ethnicity are identified as being at a heightened risk for this condition Early finding can extend life by 3-4 years. The study uses EBHI-seg dataset to explore GAN for image segmentation. DC-GAN is better than VAE-GAN is utilized for the persistence of producing artificial images. In the enhancement of neural-network models, DC-GAN demonstrated superior performance compared to VAE-GAN. The augmentation of data through GANs have significantly advanced machine learning methods cast-off for analysing medical images.. DC-GAN performed better than VAE-GAN.[9]Different types of cancer can occur simultaneously in various organs, with lung and colon cancer causing adverse effects. Cancer diagnosis involves analysing histopathological images in a complex process, which can now be expedited using available technology. [10]However, improvement is needed in classifying lung &colon cancer (LCC). A method using deep-learning was developed for LCC classification, involving three phases: pre-processing, segmentation, besides classification. Initially, histopathological images are pre-processed by applying a median filter. Segmentation using the swim transformer identifies lung nodules and colon regions. The segmented regions are served hooked on the Enhanced Cascade Convolutional Neural-Network (EC2N2) classifier to determine they are normal or cancerous.[11] The Adaptive-Tasmanian-Devil-Optimization algorithm optimally selects hyper parameters for the cascade classifier to enhance efficiency. The technique's effectiveness is evaluated through various metrics then compared with state-of-the-art works.

Cancer can develop in multiple organs, such as lung and colon, causing adverse effects. Experts use a complex process to diagnose cancer from histopathological images, which can now be done quickly with current technology. However, the classification of lung and colon cancer needs enhancement. [12]A method using deep learning was developed for this purpose, involving three phases -1.pre-processing, 2.segmentation, and 3.classification. Pre-processing involves collecting and filtering histopathological images. Segmentation is done using the swin transformer to identify lung nodules and colon. The segmented parts are classified as normal or cancerous using the EC2N2 classifier.[13] Hyper-parameters for the classifier are optimized using the ATDO algorithm. The technique's efficiency is evaluated using various metrics and compared with other research works.

Automated methods aid in analyzing medical images of colon cancer, a significant research area. Colonoscopy detects abnormalities in the colon and rectum, part of gastrointestinal diseases causing many deaths globally. Video endoscopy diagnoses gastrointestinal disorders like inflammatory bowel disease and polyps. [14]Medical specialists review numerous images from video endoscopy. Research focuses on computer-aided techniques for accurate and fast diagnosis of medical images. Proposed methodology creates a framework for analyzing coloscopy diseases. Computer-assisted polyp detection can reduce the risk of cancer during colonoscopies. A modified DeeplabV3+ model effectively segments polyps from images. The model's encoder utilizes a pre-trained expanded convolutional residual network to attain peak resolution. The refined model is evaluated against cutting-edge segmentation techniques, yielding Dice similarity scores of 0.97 and 0.95 across two datasets. The upgraded DeeplabV3+ model boosts segmentation accuracy and applicability in both software and hardware..

The resemblance in shape and consistency between colonic polyps and normal mucosal tissues results in reduced accuracy in the segmentation of medical images. A segmentation algorithm for polyp images is introduced, integrating Hard Net, attention, and multi-scale coding components within a U-Net framework. This algorithm comprises two phases of encoding and decoding, employing HarDNet68 during the encoding phase for feature extraction to enhance computational efficiency. Furthermore, an attention mechanism module is incorporated to capture both global & local feature information, addressing information loss issues and boosting the overall performance of the network.. The analysis on the compared model shows improved segmentation accuracy and operation speed, assisting medical doctors in removing abnormal colorectal tissues and reducing polyp cancer probability, thus enhancing patient survival rates and quality of life.[17] The algorithm's generalization ability provides technical provision and prevention for colon cancer

III. PROPOSED SYSTEM

The main findings of this paper are summarized.

- Developed a novel architecture named Contextual Learning Network Autoencoder (CENET) designed specifically for histopathology image segmentation.
- Integrated methods for capturing contextual information, including multi-scale features and attention mechanisms, within the CENET framework.
- Evaluated the segmentation performance of CENET using several quantitative metrics, including mean Dice Similarity Coefficient (mDSC), mean Intersection over Union (mIoU), recall, and precision.
- Assessed the effectiveness of CENET in accurately delineating regions of interest, such as tumor boundaries, in histopathology images exhibiting varied tissue characteristics and morphologies.
- Performed a comparative evaluation of CENET against existing segmentation techniques, demonstrating its improved capability for analyzing and interpreting histopathology images.

A. DATASETS

The dataset known as the Colorectal Cancer Histology Images comprises 1000 histological images concentrating on colorectal cancer. Each image inside this dataset has undergone thorough annotation for the purpose of identifying tumor areas, offering significant insights for professionals and researchers in the realms of cancer pathology and medical image analysis. Histological images are produced through the examination of stained tissue samples under a microscope, enabling the observation of cellular structures and irregularities. Concerning colorectal cancer, these images depict the minute details of tissue segments from the colon or rectum impacted by cancerous proliferation.The dataset contains annotations that outline the specific areas within each histological image that depict the existence of tumor tissue. These annotations function as authentic data, facilitating the creation and assessment of algorithms designed for the automated detection and segmentation of tumors. Histopathological Images:The histopathological images depict microscopic views of tissue samples collected from colorectal regions. They offer detailed visual insights into the cellular structures and anomalies present in the tissue.

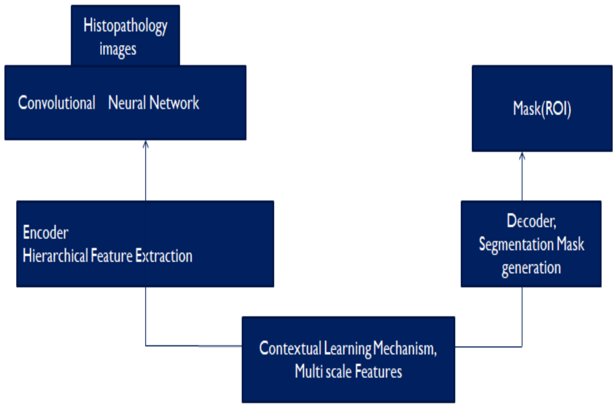

Figure1: Overall Architecture Diagram

B. Data pre-processing: During the training stage, the model underwent training using 50% overlapping patches measuring 512x512x3 in size. This approach was primarily employed to address the challenges posed by class imbalance and limited data availability

- Convolutional Neural Network (CNN): The CNN serves as the core architecture for feature extraction, consisting of convolutional layers, pooling layers, and activation functions. The convolutional layers detect patterns and features across numerous spatial scales within input images. Pooling layers decrease the spatial size of feature maps, preserving critical information. Activation functions add non-linearity, empowering the network to capture complex data patterns.
- The encoder component within the CENET framework is responsible for removing hierarchical features from the provided histopathological images. This module commonly consists of various convolutional and pooling layers that iteratively acquire abstract representations of the input images. The hierarchical features generated encompass both intricate specifics at a lower level (e.g., edges and textures) and profound semantic details at a higher level (e.g., shapes and configurations).
- Contextual Learning Mechanisms: These mechanisms enhance the encoder-decoder architecture by integrating contextual information into the feature extraction process. Multi-scale features involve processing input images at various resolutions, enabling the network to internment information at diverse scales. Attention mechanisms dynamically assign weights to different spatial locations in feature maps, enabling the network to concentrate on relevant regions and suppress noise and irrelevant data. Other contextual learning techniques may involve skip connections, spatial context modelling, and feature recalibration.
- Decoder: The decoder segment of CENET reconstructs segmentation masks from the hierarchical features extracted by the encoder. It typically comprises up sampling layers that enhance the spatial resolution of feature maps to match the original dimensions of input images. The decoder refines the features and generates pixel-wise predictions, producing segmentation masks that outline regions of interest, such as potential tumor sites.

IV. RESULTS

Segmentation Masks are binary representations that emphasize regions of interest-(ROU) within histopathological images. Each pixel in the mask is assigned a value indicating the probability of belonging to a tumor region. The segmentation masks offer valuable guidance to clinicians and pathologists by highlighting areas necessitating further scrutiny and examination. By integrating these elements, CENET effectively merges feature extraction, contextual learning, and segmentation to precisely outline tumor regions in histopathological images of colorectal tissue samples. This method facilitates early and automated detection of colorectal tumors, assisting in cancer diagnosis and treatment planning which is mentioned in the figure2.

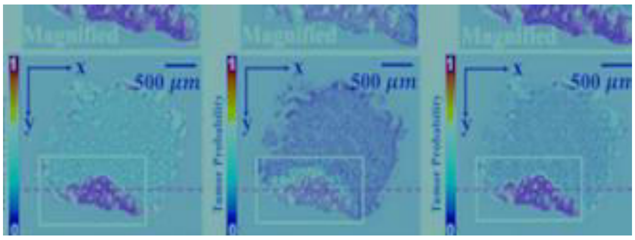

Figure 2: Segmented magnified Output

V. COMPARISON WITH EXISTING MODELS

The comparison presented in the table evaluates various image segmentation models based on metrics such as Dice Similarity Coefficient (DSC), mean Intersection over Union (mIoU), Recall, and Precision. The range of models spans from the fundamental U-Net, which exhibits moderate precision but lower performance in other metrics, to more intricate architectures like Double U-Net and FCN8, which demonstrate enhanced performance across all metrics. Particularly noteworthy is the ResUNet++ with CRF, which notably boosts segmentation capability, achieving a DSC of 0.851 and mIoU of 0.833.

Advanced models such as DeepLabv3+ and PolypSegNet further elevate these metrics, especially in mIoU and Recall, highlighting superior segmentation accuracy and efficacy. The most outstanding model is the proposed CENET, surpassing with a DSC of 0.904 and mIoU of 0.848, implying outstanding segmentation precision and overall accuracy which is mentioned in the Table1.

TABLE I:
COMPARISON OF CE MODEL PERFORMANCE

Model	mDSC	mIoU	Recall	Precision
U-Net	0.716	0.434	0.632	0.923
Double- U-Net	0.813	0.733	0.84	0.861
FCN8 (VGG16 backbone)	0.831	0.737	0.835	0.882
PSPNet (ResNet50 backbone)	0.841	0.744	0.836	0.89
HRNet	0.845	0.759	0.859	0.878
ResUNet++ with CRF	0.851	0.833	0.876	0.823
DeepLabv3+ (ResNet101 backbone) [77]	0.864	0.786	0.859	0.906
U-Net (ResNet34 backbone)	0.876	0.81	0.944	0.862
FANet	0.88	0.81	0.906	0.901
PolypSegNet	0.887	0.826	0.925	0.917
PROPOSED CENET	**0.904**	**0.848**	**0.923**	**0.907**

The illustration in figure 3 depicts a comparison of performance among different image segmentation models based on four metrics: Dice Similarity Coefficient (mDSC), mean Intersection over Union (mIoU), Recall, and Precision. The models are displayed on the x-axis, while their performance values range from 0 - 1 on the y-axis.

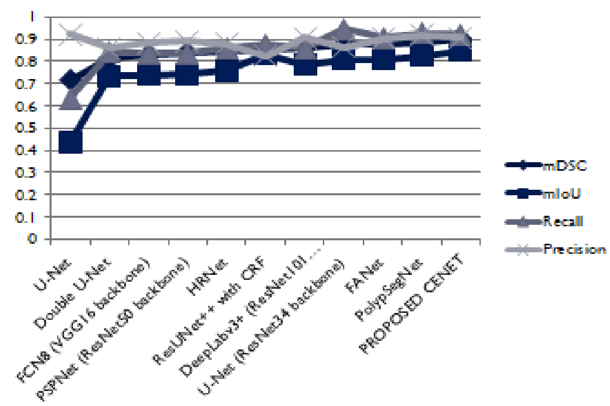

Figure 3: Comparison graph with other models

It is evident that the proposed CENET model surpasses others, exhibiting the highest scores across most metrics, except for Precision where the PolypSegNet model marginally outperforms it. A clear trend of enhanced performance is observed from U-Net to CENET. While all models demonstrate relatively high Precision, there is notable variability in mIoU and mDSC scores. Symbols are used in the graph to distinguish between the metrics, facilitating the visual interpretation of each model's comparative performance

VI. CONCLUSION

In conclusion, the CE-NET model presented in this paper demonstrates significant promise for advancing automated colorectal polyp detection and segmentation. With a mean Dice- similarity coefficient (DSC) of 0.904, mean Intersection over Union (IoU) of 0.848, recall of 0.923, and precision of 0.907, the proposed model exhibits commendable accuracy in segmenting histopathology images. By leveraging a CE-Net architecture and training on an augmented image dataset, the CE-NET model effectively addresses the challenges of automated detection and localization of colorectal polyps. Moreover, its ability to operate in real-time further enhances its utility for early-stage colorectal cancer diagnosis and treatment planning. Overall, the findings underscore the possible of the CE-NET model to contribute knowingly to the field of medical image analysis, particularly in successful outcomes for colorectal cancer patients through early detection and intervention.

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