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Segmentation Of Medical Images Using U-Net With Resnet

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Abstract: Medical image segmentation, particularly for polyps in gastrointestinal images, presents significant challenges because of variations in color and morphology observed during colonoscopy imaging. In our study, we focused on this crucial area, utilizing a dataset comprising gastrointestinal polyp images. We employed advanced deep learning techniques, specifically FCN, Dual U-Net with ResNet Encoder, U-Net, and Unet_Resnet, to tackle the segmentation task effectively. To enhance the effectiveness of these algorithms, we incorporated data augmentation techniques, which involve creating modified versions of the initial images to enrich the training dataset. We evaluated the effectiveness of these algorithms using standard metrics like Dice Similarity Coefficient (DSC) and Intersection over Union (IOU), which quantify the correctness of segmentation compared to ground truth. Among the models tested, the Dual U-Net with ResNet Encoder emerged as the most successful, achieving a DSC of 0.87 and IOU of 0.80. This model outperformed other approaches, including U-Net, FCN, and Unet_Resnet, demonstrating its superior performance in segmenting gastrointestinal polyp images.

***Index Terms* -** Unet, Resnet, Positron Emission Tomography, Computed Tomography, Convolution Neural Networks, Fully Convolution Neural Network, Rectified Linear Unit.

I. INTRODUCTION

Image segmentation stands out as a highly effective method within the realm of image analysis, which involves extracting valuable data from images by examining their features. Various image processing methods, such as edge detection, preprocessing, and segmentation, are employed to facilitate this analysis [2]. The primary objective of image analysis is to enhance images or derive pertinent information from them [20]. Segmentation, in particular, represents a pivotal yet intricate facet of image processing for analysis purposes. It involves dividing digital images into distinct segments, thereby enhancing overall image quality. Advancements in segmentation techniques are rapidly progressing, leading to more rapid and precise approaches in image analysis.[10]. Medical image segmentation, an increasingly important technique in medical image processing, has played a crucial role in advancing long-term medical care. In medical image analysis, segmentation is conducted to pinpoint specific areas of interest within images [18]. Prior to diagnosing an illness, medical images undergo several stages. Initially, images are collected, followed by preprocessing steps, and then data storage. This necessitates ample memory space and processing time. Processing medical images is essential to extract pertinent information for medical applications.[39]. Polyps in the gastrointestinal tract are irregular cell growths in the stomach and colon lining. Typically, they develop slowly and often remain asymptomatic until they reach a significant size [16]. Among the leading causes in gastroenterology is the development of polyps, which can potentially progress to colorectal cancer [25]. However, early detection of polyps can prevent and effectively treat cancer [16]. Segmentation of gastrointestinal polyps poses a challenge as a result of the diverse color intensity and shapes observed in colonoscopy images. To achieve precise segmentation, various methods have been devised and refined [1].

In this study, we applied various CNN algorithms, including Dual U-Net with ResNet encoder, U-Net, Unet_Resnet, and FCN, to perform segmentation on gastrointestinal polyp images gained from the "Kvasir-SEG" dataset. We assessed the demonstration of these algorithms using metrics such as the Dice similarity coefficient and Intersection over Union, and compared their segmentation outcomes based on these metrics.

The structure of the paper is as follows:
- Section II reviews related works pertinent to our study.
- Section III provides an overview of the architecture of the Dual U-Net with ResNet encoder.
-Section IV details the methodology employed in this study.
- Section V presents the results and associated discussions.
- Section VI concludes the study and outlines potential future directions.

II.RELATED WORK

Medical images play a critical role in monitoring and diagnosing patients' health status[27]. They are essential for diagnoses, clinical investigation and treatment planning, providing detailed interior views of the body using techniques such as X-Rays, Positron Emission Tomography (PET), Computed Tomography (CT), Ultrasound, and Magnetic Resonance Imaging (MRI). The consumption of these medical imaging methods has grown significantly due to technological advancements [32]. Medical images are characterized by their vast quantity, high resolution, and complex features [11]. They are routinely used and stored for diagnostic and research purposes [15]. Image analysis refers to the systematic examination of images to extract meaningful information. Image analysis involves extracting quantitative data from images by measuring various parameters within them. It has found significant utility in both industrial and scientific contexts, as it allows for the objective processing of digital images without altering the sample [31]. Common visual enhancement techniques used in image analysis include pre-processing, edge detection, compression, and segmentation. Pre-processing typically involves noise reduction, intensity normalization, and data enhancement before computational analysis. Image compression aims to reduce data redundancy for more efficient storage or transmission [2]. Edge detection identifies object boundaries by detecting intensity discontinuities, and it is useful for identifying regions of significant change in an image [2].Edge detection is a method used in image analysis to point out the boundaries or edges of objects within an image based on variations in intensity [29].Image segmentation, a critical step in image processing, involves dividing an image into distinct parts, each containing specific information. This process facilitates further analysis and interpretation of image content [34]. Image segmentation serves as a crucial initial step in image analysis, enabling the extraction of valuable information [17]. It involves partitioning an image into contiguous regions [19], commonly utilized to detect objects and boundaries such as lines and curves [21]. Various techniques are employed for image segmentation, including edge detection, thresholding, region-based segmentation, clustering, and deep neural network-based methods [26].In medical imaging, segmentation plays a vital role in examination and assessment, aiming to identify and isolate characteristic regions within images[18]. This method is essential for tasks such as locating tumors, detecting lesions and anomalies, aiding in treatment planning, particularly for radiation therapy, and enhancing the overall quality of medical scans [23].

Banerjee et al.[6], introduced an algorithm that divides pixels into four sections grounded on their intensity levels. This method utilizes thresholding with one global threshold and two local thresholds. A novel aspect of this approach is the automatic determination of three thresholds based on inherent image characteristics. The global threshold is computed by comparing the neighborhood of localized parts within the picture. It then divides pixels into two groups, which are used to determine the local thresholds. To assess the algorithm's effectiveness, the resulting images are compared to benchmark images from Berkeley's dataset. Visual examination confirms that all regions identified in the benchmark images are successfully detected by the recommended algorithm. Cao et al[22], introduced an algorithm designed for segmenting sequences of CT images depicting the entire heart. They devised two enhanced segmentation algorithms based on traditional region-based and edge-based approaches. These refined algorithms were then applied to segment CT visuals of the whole heart sequence. Evaluation of the planned segmentation method focused on three aspects: the algorithm's efficiency, subjective assessment of whole heart image segmentation, and the deviation method, utilizing Jaccard and Dice coefficients to evaluate segmentation outcomes. Contrast of the improved segmentation algorithms with manual segmentation results exposed that the enhanced algorithms offer superior efficiency, reliability, and accuracy in segmenting CT graphics of the entire heart.

Significant progress has been made recently in developing more efficient and accurate segmentation algorithms for medical images using ML techniques [9]. The area of machine learning has witnessed a surge in deep learning-based methods [13]. Techniques like Recurrent Neural Networks (RNNs), Artificial Neural Networks (ANNs), and Convolution Neural Networks (CNNs) have proven highly effective for image segmentation tasks. Among these, CNNs have shown particular promise for addressing medical image challenges. Convolution operations play a crucial role in CNNs, enhancing their performance in tasks such as separation and categorization in image analysis [18]. Within the realm of CNNs, various architectures exist, including AlexNet, VGG, FCN, SegNet, ResNet, and U-Net [36]. Among these, AlexNet, VGG, and ResNet are widely recognized for their effectiveness in image classification and recognition tasks [5].

A Fully Convolutional Neural Network (FCN) is a segmentation technique that predicts pixel-wise labels directly from an image's ground truth, outputting a label map. FCN aims to extract important feature maps and match them with image labels, enabling effective segmentation, object detection, and classification. However, FCN's performance heavily relies on the availability of sufficient training data, which is often limited and costly to gather in medical imaging due to privacy, regulatory, and ethical concerns [37]. Insufficient data can lead to less accurate results and inaccurate segmentation [8], particularly for smaller organs [12]. To address these limitations FCN has been improved upon by methods like U-Net for medical image segmentation, which can achieve effective results with smaller training datasets [37]. CNN architecture for image segmentation is SegNet, known for its memory efficiency and performance [14]. However, U-Net typically exhibits faster processing during training and outperforms SegNet in conditions of segmentation accuracy [4] .U-Net stands as one of the most popular deep Convolution Neural Network architectures employed for segmenting medical images [24]. Its structure consists of two main components: downsampling also recognized as the contracting path, and upsampling, referred to as the expansive path [7].

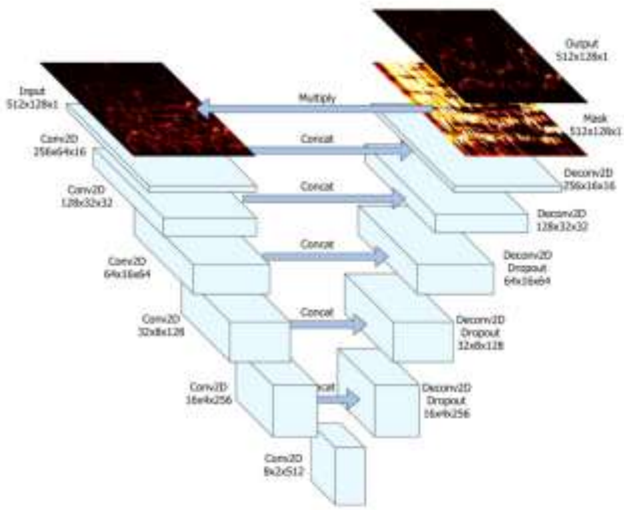

Fig 1. The architecture of U-Net [35]

Figure 1 illustrates the structure of U-Net, which comprises a contracting path (left side) and an expansive path (right side). Throughout the contracting path, a convolution network design is employed. It includes two 3x3 convolutions, each followed by a Rectified Linear Unit (ReLU) activation function, and a 2x2 pooling operation with a stride of 2 for downsampling. The add up to of channels is doubled during this downsampling process. On the other hand, the expansive path consists of a 2x2 convolution operation for reducing feature channels, concatenation with the consequent cropped feature map from the contracting path, and two 3x3 convolution layers, each followed by a ReLU activation function. Finally, a 1x1 convolution layer is used at the last layer to map the features to the required number of classes[35].U-Net architecture has garnered significant attention in medical image segmentation, leading to the development of various variants based on it[12].

In their study [30], the authors developed 3D U-Net, a convolution neural network technique, specifically for whole heart segmentation. This algorithm consists of two 3D U-Net architectures: the first part identifies the bound envelope around the heart, while the second part performs the segmentation task. The algorithm was tested on a dataset comprising 20 3D CT images, divided into 15 training images and 5 validation images due to limited data availability. To address the small dataset size, the authors employed data augmentation techniques to enlarge the training dataset's size, thereby improving the algorithm's performance. The algorithm's performance was evaluated using the Dice coefficient, a common metric for assessing segmentation accuracy. The projected model achieved a mean Dice score of 89% for whole heart segmentation.

In their work [38], the authors introduced a U-Net segmentation architecture tailored for CT images of lungs, particularly focusing on lung cancer thoracic CT scans with visible lesions. Manual segmentation of lung parenchyma was conduct to establish ground truth data prior to experimentation. Following manual segmentation, image cropping was performed to eliminate irrelevant details for analysis purposes. The show of the network was assessed using the Dice coefficient index, a common metric for evaluating segmentation accuracy. The authors achieved a Dice coefficient of 0.9502 for lung segmentation, indicating high accuracy in delineating lung regions within CT images.

III.THE ARCHITECTURE OF DUAL U_NET WITH RESNET ENCODER

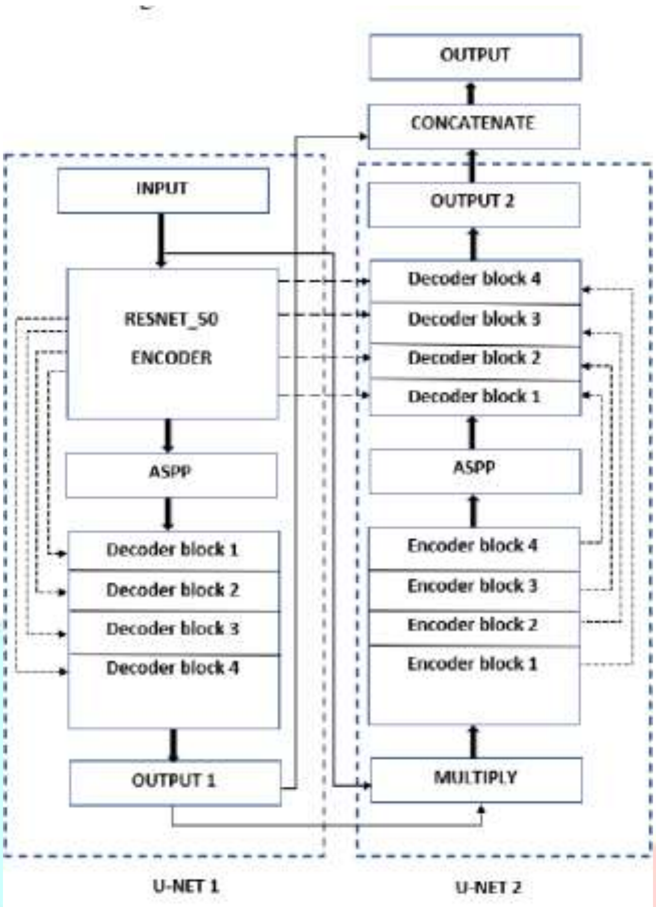

Fig 2. Architecture of dual Unet with resent encoder

Figure 2 illustrates the architecture of Dual U-Net with ResNet encoder, consisting of two U-Nets (U-NET 1 and U-NET 2) and a ResNet_50 encoder sub-network. In U-NET 1, the distinctive features include the application of ResNet_50, ASPP (Atrous Spatial Pyramid Pooling), and decoder blocks, setting it separately from the standard U-Net. Additionally, an element-wise multiplication is performed between the outputs of U-NET 1 and its input. In U-NET 2, the key difference lies in the utilize of ASPP. While the first encoder in Dual U-Net utilizes a pre-trained ResNet_50, U-NET 2 employs an encoder created from scratch. The encoder in U-NET 2 conducts two 3x3 convolution operations, followed by batch normalization and Rectified Linear Unit (ReLU) activation. Squeeze and excitation blocks are then functional to enhance feature map integrity, followed by max-pooling to reduce spatial dimensions.

The architecture incorporates two decoders, each performing 2x2 bi-linear upsampling to increase feature map dimensionality. Skip connections concatenate feature maps from the encoders with the result feature maps. The first decoder utilizes skip connections from U-NET 1, while the second decoder utilizes skip connections from both U-NET 1 and U-NET 2. After concatenation, two 3x3 convolutions, batch normalization, ReLU activation, and a squeeze and excitation block are applied. Finally, a convolution layer with a sigmoid function generates the mask.

IV.METHODOLOGY

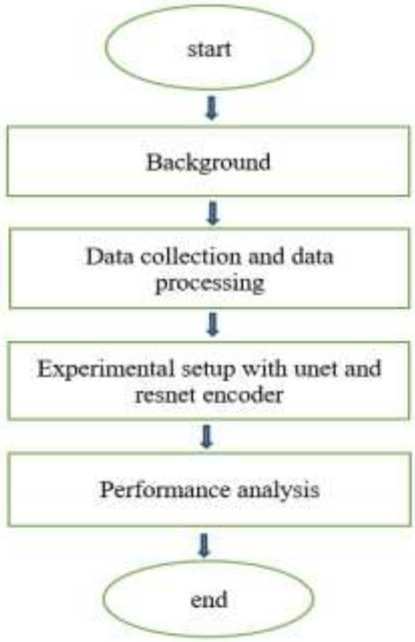

Fig 3. Illustrates the flowchart of the methodology

Figure 3 depicts the flowchart outlining the methodology employed in this study. The methodology design is structured into four stages: research design, data collection and processing, experimental setup, and performance analysis. Edge detection is a technique that finds and emphasizes the lines or boundaries between different objects or regions in an image by detecting changes in brightness or color. The dataset of gastrointestinal polyp images undergoes partitioning into three sets: a training set, a validation set, and a testing set. The training set comprises 80% of the dataset, totaling 800 images, while the validation and testing sets each contain 10%, equating to 100 images each. Following dataset partitioning, data augmentation is applied to the 800 images within the training set, expanding the total number of training dataset images to 13,600.In this study, four deep convolution neural network algorithms are utilized for image segmentation: Fully Convolution Network (FCN), U-Net, Unet_Resnet, and Dual U-Net with Resnet encoder.

A. Research Design

The initial phase involves conducting a comprehensive review of existing research using keywords such as "segmentation," "medical images," "polyp image segmentation," "deep convolution neural network," and "U-net." This literature review aims to identify the problem statement, understand the approaches previously employed, and assess their effectiveness. This section provides an overview of image segmentation, highlighting various approaches and algorithms used in medical graphic segmentation with bottomless convolution neural networks, including their advantages and limitations.

B. Data Collection and Data Processing

This section details the procedures for gathering the dataset. The dataset utilized in this study is obtained from the 'KvasirSEG' repository (https://datasets.simula.no/kvasir-seg/), which consists of Gastrointestinal Polyp images. Upon acquiring the data, each gastrointestinal polyp image is carefully examined to establish the ground truth. The dataset comprises 1000 images along with their corresponding 1000 masks.

C.Experimental Setup and Performance Analysis

This experiment is conducted using an RTX 2060 GPU with 6 GB of RAM, and the Python 3.9 software framework with Tensor Flow 2.5. All segmentation algorithms utilized in this study are trained for 50 epochs. The image segmentation algorithms, including Unet_Resnet, FCN, U-Net, and Dual U-Net with Resnet encoder, will be compared based on their performance. Performance evaluation of these algorithms for image segmentation is carried out using the Intersection over Union (IOU) and Dice Similarity Coefficient (DSC).

IV. OUTCOME AND DISCUSSION

The dataset sourced from the 'Kvasir-Seg dataset' consists of 1000 images depicting Gastrointestinal Polyps, alongside their corresponding 1000 masks. Following dataset partitioning, comprising 80% (800 images) for the training set, 10% (100 images) for the validation set, and 10% (100 images) for the testing set, data augmentation is applied to improve the training dataset. This augmentation increases the number of training images to 13,600, contributing to improved accuracy rates. Subsequently, segmentation algorithms are applied to the gastrointestinal polyp dataset. In this study, we employ Unet_resnet, Unet, FCN, and Dual U-net with Resnet encoder for image segmentation of gastrointestinal polyps.

Intersection Over Union (IOU) = (Intersection of predicted image and mask image) / (Union of predicted image and mask image)

The Dice Similarity Coefficient measures how closely the predicted image matches the mask image, indicating the stage of overlap between the two. It is a compute of similarity between two images, calculated using a specific formula. This coefficient helps evaluate the exactness of the prediction by quantifying the percentage of similarity between the predicted and actual images.

Dice Similarity Coefficient (DSC) = 2 * (Intersection of predicted image and mask image) / (Total number of pixels in predicted image + Total number of pixels in mask image)

Recall is a measure of how well the algorithm correctly identified true positive predictions compared to all actual positive instances in the dataset. It is calculated by dividing the number of true positive predictions by the sum of true positive predictions and false negative predictions. In simpler terms, recall measures the algorithm's ability to correctly identify positive instances out of all the positive instances in the dataset.

Recall = (True Positives) / (True Positives + False Negatives)

True positive is the number of instances where the algorithm correctly identified a positive outcome. The denominator in the formula includes both the true positive cases and the false negatives, which are cases that were actually positive but incorrectly predicted as negative by the algorithm.

Precision is the calculate of how many of the items predicted as positive are actually positive. It calculates the ratio of true positive predictions to all positive predictions.

Precision = (True Positives) / (True Positives + False Positives)

A. Result

In this study, we utilized advanced convolutional neural network models such as Unet_Resnet, Dual U-net with Resnet encoder, FCN, and U-net to accurately segment gastrointestinal polyps in medical images. The presentation of these models was evaluated using two metrics - Intersection over Union (IOU) and Dice Similarity Coefficient (DSC), which measure the overlap between predicted and ground truth segmentations. These metrics provide a score between 0 and 1, with higher values indicating better segmentation accuracy. The results obtained with these models are visually displayed in Figure 4, showcasing the effectiveness of

Unet_Resnet, Dual U-net with Resnet encoder, FCN, and U-net in accurately segmenting gastrointestinal polyps in medical images.

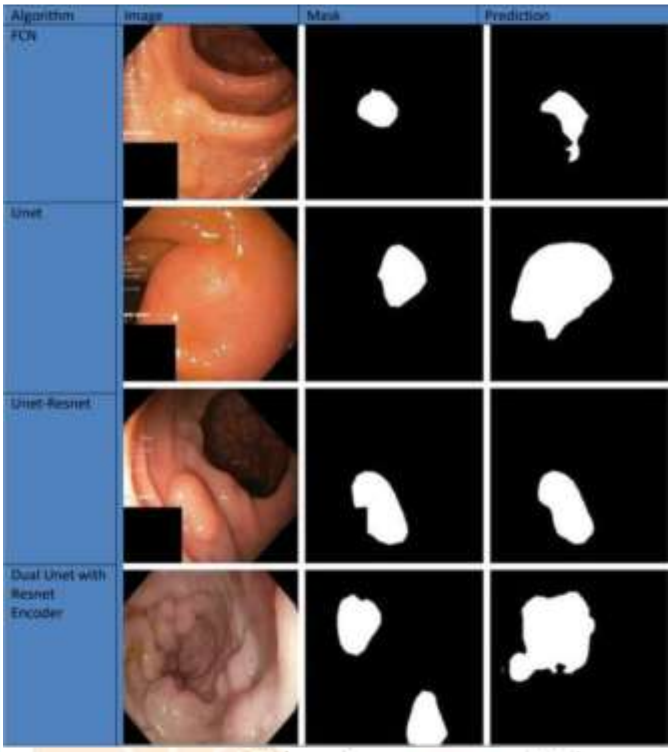

Fig 4. Result of FCN U-NET, unet_resnet and dual U-net with resnet encoder

The performance of four algorithms was compared using the Dice similarity coefficient (DSC) and Intersection over Union (IOU) metrics in Table I. The results indicate that FCN performed worse than U-Net, while U-Net_Resnet outperformed U-Net. Dual U-Net with Resnet encoder achieved the highest DSC and IOU scores among the four algorithms.

TABLE I. THE PERFORMANCE OF ALGORITHMS

Algorithm	**Dice Similarity Coefficient (DSC)**	**Intersection Over Union (IOU)**
FCN	0.9384	0.7324
U-NET	0.7937	0.7560
Unet_Resnet	0.8504	0.7669
A model combining Dual U-Net architecture with a ResNet encoder.	0.9924	0.8150

V. CONCLUSION

In this study, different deep convolution neural network models were developed to segment images of gastrointestinal polyps from the Kvasir-SEG dataset. The dataset was split into training, validation, and test sets, with augmentation techniques used to enhance performance. The models were evaluated using metrics like Intersection Over Union (IOU) and Dice Similarity Coefficient (DSC). The Dual U-net with Resnet Encoder model achieved the highest DSC and IOU scores of 0.8715 and 0.8042, outperforming other models like FCN, U-Net, and Unet_Resnet. Future work will focus on improving segmentation accuracy and applying the algorithm to different medical image datasets.

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