Dual U-Net with Resnet Encoder for Segmentation of Medical Images

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***Abstract*—Segmentation of medical images has been the most demanding and growing area currently for analysis of medical images. Segmentation of polyp images is a huge challenge because of the variability of color depth and morphology in polyps throughout colonoscopy imaging. For segmentation, in this work, we have used a dataset of images of the gastrointestinal polyp. The algorithms used in this paper for segmentation of gastrointestinal polyp images depend on profound deep convolutional neural network architectures: FCN, Dual U-net with Resnet Encoder, U-net, and Unet_Resnet. To improve the performance, data augmentation is performed on the dataset. The efficiency of the algorithms is measured by using metrics such as Dice Similarity Coefficient (DSC) and Intersection Over Union (IOU). The algorithm Dual U-net with Resnet Encoder obtains a higher DSC of 0.87 and IOU of 0.80 and beats the other algorithms U-net, FCN, and Unet_Resnet in segmentation of gastrointestinal polyp images.**

Keywords*—*Segmentation; Medical Images; Deep Convolutional Neural Network; FCN; U-net; Unet_Resnet; Dual U-net with Resnet Encoder

I. INTRODUCTION

Image segmentation is one of the most widely and effectively used techniques for image analysis. Image analysis is a method of extracting data from images by analyzing the features within an image. There are a variety of image processing techniques that are used for image analysis, including edge detection, image preprocessing, and image segmentation[1]. The fundamental purpose of image processing is to improve the image or extract relevant information from the images[2]. Segmentation is a crucial yet challenging aspect of image processing for image analysis. Image segmentation techniques are now evolving in a faster and more precise approach[3]. Segmentation is the technique of splitting digital images into several segments to improve image quality.

Segmentation of medical images, as an emerging medical image processing method, has made a significant contribution to long-term medical treatment. For analysis of images in medical, segmentation is performed to locate the area of interest[4]. Before an illness could be diagnosed, medical images must go through numerous processes. Initially, images are gathered, then the pre-processing is performed and after that data must be stored in memory. That demands a significant memory space and a processing time. It is required to process images in medical applications in order to find relevant information[5].

Polyps in the gastrointestinal are abnormal growths of cells in the stomach and colonic mucosa. This abnormal growth occurs gradually and, in most instances, it does not create symptoms till it achieves a significant magnitude[6]. One of the most common causes of gastroenterology is a polyp, which could develop into colorectal cancer[7]. Nonetheless, cancer is preventable and treated, if polyps are diagnosed early[6]. Segmentation of gastrointestinal polyps is a challenging process because of the variation in color intensity and form of gastrointestinal polyps in colonoscopy images. Various techniques have been developed in order to achieve accurate segmentation[8].

In this work, we have applied Deep Convolutional Neural Network algorithms including Dual U-Net with Resnet encoder, U-Net, Unet_Resnet, and FCN to do segmentation on the images of gastrointestinal polyps gathered from the dataset of ‘Kvasir-SEG’. The performances are evaluated by using the metrics: Dice similarity coefficient and Intersection over Union. Also, the comparison of these algorithms of segmentation is performed on the bases of metrics.

The rest of the paper is structured as follows: Section II discusses the works related to our study; Section III gives overview of architecture of Dual U-Net with Resnet encoder; Section IV explains the design of methodology for this work; Section V presents the result and discussion; Section VI gives conclusion and presents the future work.

II. RELATED WORK

Medical images are crucial and assume a fundamental part in monitoring and diagnosing the status of a patient’s wellbeing[9]. For clinical investigation, diagnosis, and treatment planning, medical imaging including X-Rays, Computed Tomography (CT), Positron Emission Tomography (PET), Ultrasound, and Magnetic Resonance Imaging (MRI) are utilized to provide a clear depiction of the interior of the body[10]. The use of medical imaging techniques has expanded in recent years as a result of technological advancement[11]. Medical images have rich properties, these are images that include a massive amount, high resolution, and complicated features[12]. These medical images are utilized and saved for diagnostic and research purposes on a regular basis[13].

Image analysis is described as a process of extracting quantitative information from images by measuring objects within them. Image analysis has proven particularly valuable for industrial and scientific applications due to its capacity to

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process digital images and objectively analyze parameters such as distance, size, color, number of particles, and so on without affecting the sample[14]. For image analysis, the major image processing approaches used are pre-processing, edge detection, compression, and segmentation. Pre-processing of images often entails eliminating low-frequency background noise, leveling the intensity of individual particle images, and erasing or improving data images before the computational processing. Image compression is a type of data compression in which the original image is encoded with a few number of bits The aim of image compression is to eliminate the image redundancy and store or transmit data in a more efficient manner[1]. Edge detection is a technique for detecting the boundaries of objects or regions that are closely related. The discontinuity of the object is identified using this technique. The edge detection technique is mostly used in image analysis to identify areas of an image where there is a large fluctuation in intensity[15]. Image segmentation is one of the primary phases of image processing where each image is partitioned into several parts, each of which contains some type of information[16].

Image segmentation is an important step in analyzing an image. Image segmentation is the first step in analyzing and extracting information from images[17]. Image segmentation is an image processing technique that partitions an image into contiguous parts[18], that is commonly used to detect objects and borders in images such as lines, and curves[19]. The various segmentation techniques for image segmentation are edge detection, thresholding method, region-based segmentation, clustering-based segmentation[20], and deep neural network-based segmentation[21]. Segmentation of medical images is an essential phase in the examination and evaluation process. For medical images, segmentation is performed to identify and extricate characteristic regions. The purpose of the segmentation of medical images is to identify the tumor location, detect the lesion and other abnormalities, help in treatment planning prior to radiation treatment[22], and help in improving the quality of medical images[4].

Banerjee, et al. [23], proposed an algorithm that clusters pixels into four sections depending on their intensity. This approach employs a thresholding mechanism with one global threshold and two local thresholds. The new aspect of this procedure is the automated establishment of three thresholds based on inherent features of the image. The global threshold is calculated by comparing the neighborhood of the image's localized parts. The global threshold divides pixels into two sets of groups, which are then used to determine the local thresholds. For evaluation of the efficiency of the proposed algorithm, the resulting images are compared to Berkeley's dataset benchmark image. The results are visually examined to determine the region identified by the proposed algorithm. All the regions mentioned in the benchmark images are successfully identified by the proposed algorithm.

Cao, et al. [24], proposed an algorithm for segmentation of the sequence of CT images of the whole heart. They have developed two improved segmentation algorithms based on traditional region-based and edge-based segmentation algorithms and then the improved algorithms are implemented to the whole heart CT sequence images for segmentation. The evaluation of the proposed segmentation algorithm is based on three features in this study: the algorithm's efficiency, subjective evaluation of whole heart image segmentation, and the deviation method, in which the Jaccard and Dice coefficients are used to evaluate the segmentation results of the whole heart CT images. The results of the two improved segmentation algorithms are contrasted with the manual segmentation results, the improved algorithms of segmentation demonstrate superior efficiency in terms of reliability and accuracy of CT image segmentation of the whole heart.

Substantial advancement has been accomplished in recent years in establishing more productive and precise segmentation algorithms for the medical image in machine learning[25]. The machine learning field has been overpowered with a variety of deep learning-based techniques. Deep learning-based techniques such as Recurrent Neural Networks (RNNs), Artificial Neural Networks (ANNs), and Convolutional Neural Networks (CNNs) are efficient in image segmentation[26]. Convolutional Neural Network (CNN) works well on medical image challenges, convolutional plays an important role in performance in CNN in image analysis techniques such as segmentation and classification[4]. In a deep neural network, Convolutional Neural Network has several architectures. AlexNet, VGG, FCN, SegNet, Resnet, and U-Net are some of the architectures of Convolutional Neural Networks[27]. AlexNet, VGG, and Resnet are widely regarded as the most prevalent architecture that successfully performs image classification and image recognition tasks[28].

A Fully Convolutional Neural Network (FCN) is a segmentation method that can make a prediction on the bases of pixel-by-pixel using the image's ground truth and directly output the label map. The objective of FCN is to extract significant feature maps and restore them to the labels of the image. The capability to identify features is the fundamental cause of FCN's effectiveness in image segmentation, object detection, and classification. FCN can function effectively only if a sufficient amount of training datasets is accessible. Data gathering is costly in the realm of medical imaging. Furthermore, there are several other aspects that affect data availability, such as privacy, regulation, and ethical concerns[29]. Without enough availability of dataset, FCN provides less accurate results[30] and results in inaccurate segmentation of small organs[31]. As a consequence, FCN has been enhanced to U-Net in order to conduct medical image segmentation, which performs effectively with a relatively small amount of training dataset[29]. SegNet is another architecture of CNN for the segmentation task of images, this architecture has significant features of memory and efficient performance[32]. However, during the training phase, U-Net exhibits a faster processing speed[33], and also U-Net performs better compared to the SegNet[34].

U-Net is among the most widely used architectures of deep Convolutional Neural Networks for segmentation tasks of medical images[35]. The downsampling (contracting path), and the upsampling (expensive path) are the primary components of the U-Net network[36]. The U-Net architecture is shown in Fig. 1.

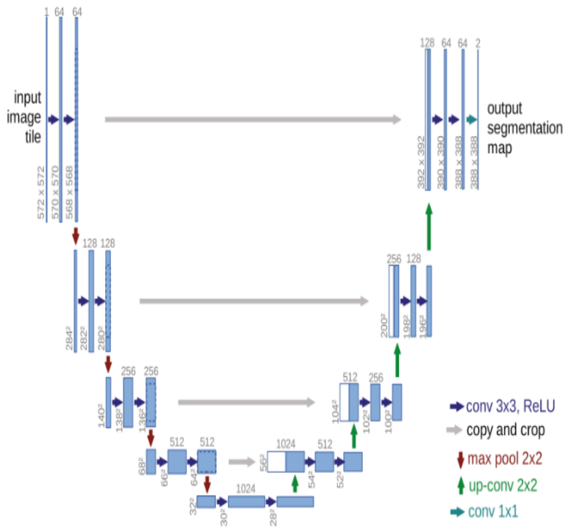

Fig. 1. The architecture of U-Net [37].

Fig. 1 depicts the architecture of U-Net which comprises of a contracting path/downsampling (left side) and an expansive path/upsampling (right side). The convolutional network design is followed throughout the downsampling path. It consists of two 3x3 convolutions, each of which is accompanied by an activation function, a rectified linear unit (ReLU), and a 2x2 pooling with stride 2 for downsampling. The number of channels gets doubled during downsampling. The upsampling or expansive path comprises of 2x2 convolutional that reduces the feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and it also has two 3x3 convolutional layers, each of which is trailed by Rectified Linear Unit activation function. At the final layer, a 1x1 convolutional layer is utilized to map the features to the necessary number of classes[37]. The U-Net architecture has sparked a lot of attention in medical image segmentation, and various variants have been developed based on it[31].

In [38], the authors developed a 3D U-Net, a convolutional neural network technique, for whole heart segmentation. The proposed algorithm comprises two 3D U-Net architectures, the first part of architecture locates the bounding box around the heart and the second part of architecture is to perform the segmentation. This algorithm is evaluated on 20 3D CT images. The dataset of 20 2D CT images is partitioned into two sets: 15 training images and 5 validation images. Because of less dataset, the augmentation procedure is utilized to increase the amount of dataset for training to increase the performance. The performance of the algorithm is calculated by using the Dice coefficient. The mean dice score of 89% is obtained by the proposed model for the whole heart segmentation.

In [39], the authors proposed a U-net segmentation architecture for the CT images of lungs. The dataset presented includes lung cancer thoracic computed tomography (CT) scans with depicted lesions. For the ground truth, manual segmentation for lung parenchyma was performed prior to the experiment. Cropping of images is conducted after manual segmentation to remove details that are not relevant for their analysis. The network's performance is evaluated by the dice coefficient index. They have achieved a 0.9502 dice coefficient for the segmentation.

III. Architecture of Dual U-Net with Resnet Encoder

The architecture of Dual U-Net with Resnet encoder is illustrated in Fig. 2.

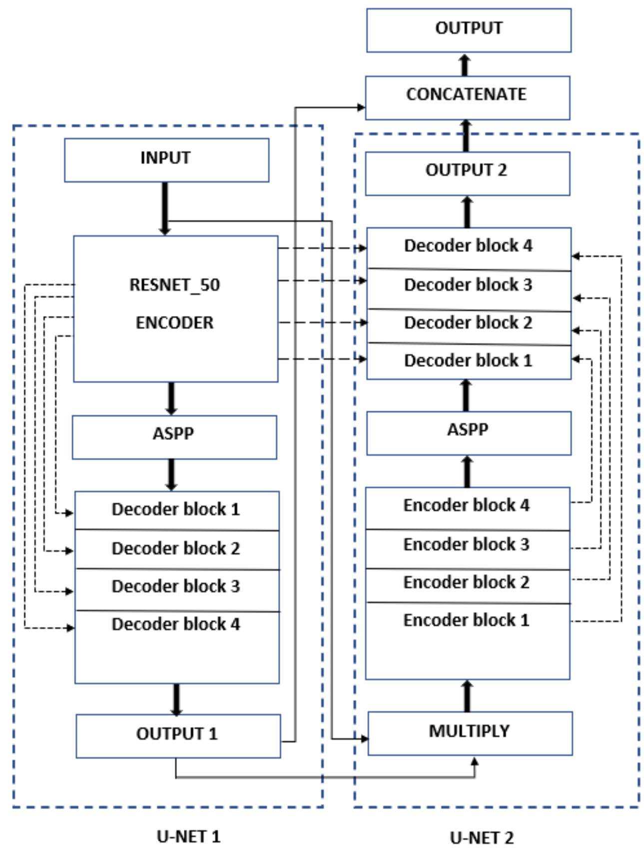

Fig. 2. Architecture of dual U-Net with resnet encoder.

Fig. 2 depicts the architecture of Dual U-Net with Resnet encoder. This architecture consists of two U-net: U-NET 1 and U-NET 2, and an encoder Resnet_50 sub-network. In U-NET 1, the application of Resnet_50, ASPP, and decoder block differentiates the Dual U-Net with Resnet encoder from U-Net. An element by element multiplication is carried out between the results of U-NET 1 with the input of the same network. In U-NET 2, the main distinction between U-Net and Dual U-Net with Resnet encoder is the use of ASPP. The first encoder in Dual U-Net with Resnet encoder purposes pre-trained Resnet_50, while the encoder in U-NET 2 was created from the beginning. The encoder U-NET 2 performs two 3x3 convolution operations, each of which is followed by a batch normalization. An activation function Rectified Linear Unit (ReLU) is applied, which is accompanied by a squeeze and excitation block, significantly improving the integrity of the feature maps. Max-pooling is applied after that with a stride2 and 2x2 window to minimize the spatial dimension of the feature maps. In the architecture, two decoders are used in Dual U-net with Resnet encoder. In the decoder, the input feature is subjected to a 2 × 2 bi-linear up sampling in every block, which increases the dimensionality of the maps of input feature. The appropriate skip connections now concatenate feature maps from the encoder with the result feature maps. Only the skip connection of the encoder in U-NET 1 is utilized in the first decoder, while the skip connection from U-NET 1 and U-NET 2 encoders is utilized in second decoder. After concatenation, two 3 × 3 convolution is performed again, each accompanied by batch normalization and a rectified linear unit activation function. A squeeze and excitation block is then applied. Finally, a convolutional layer is applied with a sigmoid function that produces the mask.

IV. METHODOLOGY

Fig. 3 illustrated the flowchart of the method utilized in this work. The methodology design for this work is divided into the following four stages: research design, data collection and data processing, experimental setup, and performance analysis.

A. Research Design

The first step is to measure and evaluate the previous research that has been investigated using the terms 'segmentation', 'medical images', 'polyp image segmentation', 'deep convolutional neural network', and 'U-net'. To identify the problem statement and determine the approaches that have been used, a literature review is required. This section gives an overview of the segmentation of images and identifies the various image segmentation approaches and algorithms, along with their merits and limitations, that have been presented for medical image segmentation using deep convolutional neural networks.

B. Data Collection and Data Processing

This section explains the process for the collection of a dataset. The dataset for this study is gathered from the 'Kvasir-SEG https://datasets.simula.no/kvasir-seg/', which contains Gastrointestinal Polyp images. Once the data is gathered, every image of gastrointestinal polyps is examined for the ground truth. The dataset of gastrointestinal polyps includes 1000 images and corresponding 1000 masks.

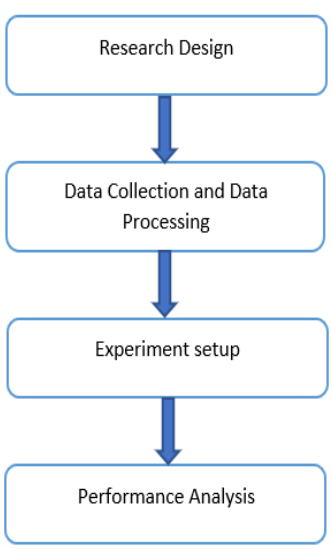

Fig. 3. Illustrates the flowchart of the methodology.

The dataset of gastrointestinal polyp images is partitioned into a training set, a validation set, and a testing set. The training set includes 80% of a dataset which is 800 images, the validation set contains 10% which is 100 images, and the testing set contains 10% which is 100 images. Once the partition of the dataset is done, augmentation of data is performed to the 800 images of the training set, increasing the total number of images in the training dataset up to 13600. For this work, we have used four algorithms of the deep convolutional neural network: Fully Convolutional Network (FCN), U-net, Unet_Resnet, and Dual U-net with Resnet encoder to illustrate the segmentation of an image dataset.

C. Experimental Setup and Peformance Analysis

This experiment is conducted on RTX 2060 GPU with 6 GB of RAM, and python 3.9 software framework with Tensor flow 2.5. All the segmentation algorithms used in this work are trained for 50 epochs.

Image segmentation algorithms such as Unet_Resnet, FCN, U-net, and Dual U-net with Resnet encoder will be compared on the basis of performance. The performance of these algorithms for image segmentation is measured by using the Intersection over Union (IOU), and Dice Similarity Coefficient (DSC).

V. RESULT AND DISCUSSION

The dataset from the 'Kvasir-Seg dataset' of a Gastrointestinal Polyps includes 1000 images of polyps and corresponding 1000 masks. Dataset is partitioned into 80% (800 images) of the training set, 10% (100 images) of the validation set, and 10% (100 images) of the testing set. After the dataset partitioning, data augmentation is implemented to the 800 images of the training set, which increases the dataset of training images to 13,600 images which will help in improving the accuracy rate. After that, the algorithm for segmentation is performed on the gastrointestinal polyp dataset. In this work, we have implemented Unet_resnet, U-net, FCN, and Dual U-net with Resnet encoder to conduct segmentation on images of gastrointestinal polyps.

The performance of the algorithm for segmentation of the images on the gathered dataset is described in this work. Performance of the algorithm is evaluated by, Intersection Over Union (IOU), Dice Similarity Coefficient (DSC) Recall, and Precision. Jaccard index commonly referred to as Intersection Over Union (IOU), is utilized to quantify the percent of overlap between the predicted image and the mask image. To calculate Intersection Over Union, the formula is as follows

$$\mathrm{IOU} = \frac{|X \cap Y|}{|X \cup Y|} = \frac{|X \cap Y|}{|X|+|Y|-|X \cap Y|} \quad (1)$$

Dice Similarity Coefficient quantifies the percentage of similarity between the predicted image and the mask image. The Dice similarity coefficient (DSC) is calculated by using the formula described below.

$$\mathrm{DSC} = 2 \times \frac{|X \cap Y|}{|X|+|Y|} \quad (2)$$

Precision calculates the percentage between the accurate prediction and the overall prediction. The following is the precision formula:

$$\text{Precision} = \frac{TRUE\ POSITIVE}{TRUE\ POSITIVE + FALSE\ POSITIVE} \quad (3)$$

The quantity of predictions that the algorithm predicted accurately is True Positive, and the total number of predictions is calculated by the formula's denominator.

Recall describes the number of accurate predictions to total observations made by the algorithm. The following is the recall formula.

$$\text{Recall} = \frac{TRUE\ POSITIVE}{TRUE\ POSITIVE + FALSE\ NEGATIVE} \quad (4)$$

True positive is the number of accurate predictions which is recognized by the algorithm, the formula's denominator shows the true positive as well as the number of positives that the algorithm falsely predicted as negative.

A. Results

The deep convolutional neural network algorithms: Dual U-net with Resnet encoder, Unet_Resnet, U-net, and Fully Convolutional Network (FCN) are used in this work to do the segmentation of the image dataset of gastrointestinal polyps. The performance of these algorithms is calculated by the Intersection over Union (IOU), and Dice Similarity Coefficient (DSC) as shown in equation (1) and equation (2) respectively. Both the metrics, Dice Similarity Coefficient and Intersection Over Union, ranges from 0 to 1. Fig. 4 illustrates a few of our results with Unet_resnet, Dual U-net with Resnet encoder, FCN, and U-net.

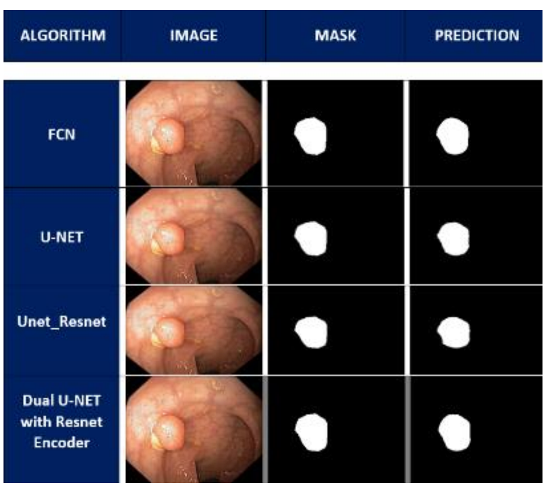

Fig. 4. Results of FCN, U-NET, Unet_Resnet, and Dual U-net with Resnet encoder.

Fig. 4 depicts the results of the segmentation of gastrointestinal polyp images using four algorithms. Table I shows a comparative study of the performances of these four algorithms.

Table I compares the performances of four algorithms based on Dice similarity coefficient (DSC) and Intersection over Union (IOU). As shown in the performance table FCN achieves less result than U-Net, while Unet_Resnet achieves a better result than U-Net. Dual U-net with Resnet encoder has achieved higher DSC and IOU than the other three algorithms.

TABLE I. THE PERFORMANCE OF ALGORITHMS

Algorithm	Dice Similarity Coefficient (DSC)	Intersection Over Union (IOU)
FCN	0.8393	0.7243
U-NET	0.8528	0.7458
Unet_Resnet	0.8603	0.7570
Dual U-net with resnet encoder	**0.8715**	**0.8042**

VI. CONCLUSION

In this work, deep convolutional neural network algorithms; U-Net, FCN, Unet_Resnet, and Dual U-net with Resnet encoder, are proposed to do segmentation of images of the gastrointestinal polyp's dataset from the Kvasir-SEG. The dataset collected from Kvasir-SEG is divided into three sets that are training set, validation set, and test set. Augmentation is applied to the training dataset, which increases the number of images in the dataset, and helps to improve the performance. The performance of the four algorithms of segmentation proposed in this work is evaluated by using the Intersection Over Union (IOU) and Dice Similarity Coefficient (DSC) metrics. Dual U-net with Resnet Encoder achieved DSC and IOU of 0.8715 and 0.8042 respectively. The result of the Dual U-net with Resnet encoder is compared with the other three algorithms, FCN, U-Net, and Unet_Resnet. FCN attained a DSC of 0.8393 and IOU of 0.7243. U-Net obtained DSC of 0.8528 and IOU of 0.7458 and Unet_Resnet acquired DSC of 0.8603 and IOU of 0.7570. The comparison result clearly shows that Dual U-net with Resnet Encoder outperforms the other three segmentation algorithms for gastrointestinal polyp images. In addition, future work will concentrate on enhancing the segmentation algorithm so that more accurate results will be achieved, and segmentation will be performed on various medical image datasets.

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