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GI TRACE IMAGE SEGMENTATION WITH UNET KERAS

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ABSTRACT

Advancements in medical imaging have paved the way for innovative solutions in diagnosing and treating gastrointestinal (GI) tract-related disorders. Image segmentation, a crucial step in medical image analysis, plays a vital role in identifying and delineating specific regions of interest within these images. This project focuses on the development and implementation of a deep learning based approach for GI tract image segmentation, utilizing the U-Net architecture with the Keras framework. The U-Net architecture has proven to be highly effective in biomedical image segmentation tasks due to its ability to capture both local and global features. The proposed model is trained on a curated dataset of GI tract images, encompassing a diverse range of anatomical structures and pathologies. The training process involves optimizing the model using a combination of loss functions tailored for segmentation tasks, such as dice coefficient loss and binary cross-entropy. The paper aims to achieve accurate and reliable segmentation results, enabling clinicians to obtain detailed insights into the structure and composition of the GI tract. The system's performance is evaluated through quantitative metrics, including precision, loss, and Dice similarity coefficient, and compared against existing segmentation methods.

In order to enhance cancer treatment and reduce radiation exposure, radiation oncologists work to deliver high doses of radiation to the tumor while avoiding the stomach and intestines on MRI images. Correctly segmenting the stomach and intestines is the goal of this task. It is a time-consuming and physically demanding task for a radiation oncologist to hand draw the location of the stomach and intestine. If the stomach and intestines could be segmented using advanced tools and technology like that of deep learning models, this treatment may be finished sooner and more patients might get better care. This paper proposes a deep learning-based model to segment gastrointestinal tract (GI) magnetic resonance images (MRI). The application of this model will be useful in potentially accelerating treatment times and possibly improve the quality of the treatments for the patients who must undergo radiation treatments in cancer centers. This paper proposes a deep learning-based model to segment gastrointestinal tract (GI) magnetic resonance images (MRI). The application of this model will be useful in potentially accelerating treatment times and possibly improve the quality of the treatments for the patients who must undergo radiation treatments in cancer centers.

1. INTRODUCTION

Cancer diagnosis and treatment is a challenging task for many healthcare professionals. Millions of people every year undergo many forms of treatments to help reduce the symptoms of the specific cancer they have, and in some cases, they are able to overcome the sickness altogether. A common form of cancer treatment is radiation therapy, where the patient receives radiation through a beam that targets the cancerous cells, while unfortunately also affecting a certain number of healthy cells around the cancer. Radiation oncologists and therapists make use of a highly advanced imaging system, Magnetic Resonance Imaging Guided Linear Accelerator (MR Linac) [1], to get clear and accurate images of the position of the patient's organs and tumor. The imaging is done daily, and they must manually outline the organs in the dosage area so that they can plan and compute an effective angle and dosage of radiation to deliver to the tumor. This treatment therefore requires careful planning and organization to ensure the radiation can be safely and consistently delivered to the patient on a regular basis.

Image segmentation and processing form the basis of many computer vision studies [1]. The concept of representing an image in a matrix of numbers and its division into several segments homogeneously has resulted in the development many state-of-the-art algorithms for processing and inference. Also, integrating deep learning techniques for prediction with computer vision and the high computational specifications of today's systems have resulted in the development of proficient systems yielding high-performance results for medical image segmentation.

2. RELATED RESEARCH OVERVIEW

Automated medical image segmentation has always been a pioneering topic of research amidst researchers since the 19th century. One of the earliest proposed solutions includes the application of edge-preserving filters and active contour models [1]. The subsequent solutions proposed for noise removal and effective segmentation of medical images include particle filtering [2], bilateral filtering [3], and diffusion filtering [4]. However, the rise of deep learning and the enhanced computational capacity of present-day computers have replaced the traditional machine learning applications involving the usage of handcrafted features [5]. The evolution of deep learning and efficient image processing techniques have paved the way for state-of-the-art solutions for identifying the desired pixels of both organs and lesions with

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minimal background noise. In the following aspects of this section, the overview of the different techniques involved in the segmentation is presented. The concept of fuzzy clustering involving the presence of a data point in more than one cluster has gained significance in many deep learning classification tasks today. Keeping this view, Devnathan et al. [7] proposed a Fuzzy C-Means clustering technique validated on the ISIC-2018 Skin Lesion dataset [2]. The proposed algorithm showed a significant improvement in performance as compared to the Superpixel-based Segmentation algorithm. Similarly, Beddad et al. [6] proposed a spatial fuzzy C-means Clustering method for removing noise and heterogeneous intensity pixels.

UNET TYPE NETWORKS: A U-Net is a type of convolutional neural network (CNN) architecture commonly used in image segmentation tasks. It was originally designed for biomedical image segmentation but has found applications in various fields, including computer vision and medical image analysis. The name "U-Net" comes from the network's U-shaped architecture. Here are key features and characteristics of U-Net type networks: Encoder-Decoder Architecture: U-Net consists of an encoder-decoder structure. The encoder captures context and extracts features from the input image, while the decoder reconstructs the spatial information and generates a segmentation map. Contracting Path (Encoder): The encoder typically contains several convolutional and pooling layers, creating a "contracting path." This part of the network reduces spatial resolution and extracts hierarchical features. Expansive Path (Decoder):The decoder, also known as the expansive path, involves up sampling and concatenation operations to gradually increase the spatial resolution. This path refines the segmentation map and generates a detailed output.

Up until 2014, the performance of the state-of-the-art methods for object detection performance, as measured by the PASCAL VOC (Visual Object Challenge) dataset, seemed to have plateaued. However, in the paper Rich feature hierarchies for accurate object detection and semantic segmentation [4], Girshick et al. introduced an approach where they apply high capacity CNNs to bottom-up region proposals to localize / segment objects and utilize domain-specific fine-tuning after performing a supervised pre-training-for-an auxiliary task in cases where labeled training data is scarce. Girshick et al. called their novel proposed method, which combines region proposals with CNNs, Regions with CNN features, or R-CNN. RCNN consists of three modules. As described in the paper, the first generates region proposals that are category independent, the second extracts a feature factor from each region using a large CNN, and the third utilizes a set of class specific linear SVMs.

Preprocessing :

Upon observing the dataset, we notice that it contains images that are ambiguous and show little visual information through the scan. So we first preprocess the dataset by obtaining only the images that have sufficient visual information. Further observing and processing the image sizes present in the dataset, we notice that the most common size across all these images (67.33% occurrence) in the dataset is 266 × 266 and the rest of the images are of sizes 310×360, 276×276, and 234×234 in frequency descending order. In order to create masks for segmented areas, we also have to ensure the sizes of images are the same, so we reshape all images to size 256 × 256 as it is a power-of-two number (required in evaluation calculation) that is closest to the current image sizes. After resizing the images, we then scale the RLE encoded segmentation masks accordingly for masks to cover the same corresponding regions in each MRI scan as prior to reshaping. Moreover, since the training labels are 16-bit RLE-encoded masks that are less interpretable visually, we convert them into pixel values and visualize the labeled areas by highlighting the masks and drawing bounding boxes around the region. In order to feed the image, mask, and target into training models, we also process them as tensors and store them in separate files which will allow us to obtain the information simply by loading the preprocessed files. Finally, we split up the complete dataset into training, validation, and testing sets by 70%, 20% and 10% respectively.

3. RESULTS

PARAMETER	PREVIOUS RESULT	CURRENT RESULT
1.LOSS	0.8530-epoch1	0.0842-epoch1
	8.5457-epoch2	0.0836-epoch2
	0.3614-epoch3	0.0772-epoch3
	0.2842-epoch4	0.0766-epoch4
2.DICE COEFFICIENT	0.2301-epoch1	0.8474-epoch1
	0.4908-epoch2	0.8485-epoch2
	0.6630-epoch3	0.8599-epoch3
	0.7345-epoch4	0.8610-epoch4

4. CONCLUSION/FUTURE WORK

The presented approach is effective for detecting cancerous tumors in the Gastro-Intestinal Tract through segmentation The segmentation helps to administer radiation therapy without harming other organs Accurate segmentation of the abdominal region is crucial for this task Future research can focus on developing algorithms that can spot tumors based on segmented images. In this paper, we survey different strategies for segmenting, which will help design an algorithm that can be used to segment the Gastro-Intestinal (GI) tract in order to identify malignant tumors in the specific abdominal region. By doing so, radiation therapy can be administered without endangering other organs. Here, it is emphasized how important it is to segment the abdomen area precisely. This could serve as the foundation for future research into creating algorithms that can detect malignancies based on segmented images.

The model described in this paper managed to achieve a promising performance that could prove useful for helping radiation therapists in segmenting organs in the scans taken of patients on a daily basis. The benefits of this model will not only affect the lives of the radiation therapists, but also the patients they treat by improving wait times and quality of the treatment itself. Finally, with the reduced treatment times for each patient, cancer clinics will naturally be able to accept a higher volume of patients per day and people diagnosed with cancers in the GI tract will be able to get treatment more quickly. All these benefits mean that people diagnosed with this kind of cancer can have a higher chance of survival with fewer side effects. In the Future, the model will be further tuned to provide a better performance score. This tuning phase will consider different network layouts as well as hyper parameters tuning. Furthermore, the model could be used as a stepping stone towards creating more models to segment other organs of the body to help therapists with treating other kinds of cancer.

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