Efficient U-Net Architecture with Multiple Encoders and Attention Mechanism Decoders for Brain Tumor Segmentation

Summarize this text : Brain tumors account for 85% to 90% of all primary central nervous system (CNS) tumors. Worldwide, an estimated 308,102 people were diagnosed with a primary brain or spinal cord tumor in 2020. Two years later, the number increased to 700,000 in the United States, and approximately 88,970 more will be diagnosed according to the national brain tumor society (NBTS). Globally, over 241,000 die each year because of brain tumors or nervous system cancer and each year the number of people who die increases. Glioma is one of the most common types of brain tumor and is also known as a primary brain tumor. Although the exact origin of gliomas is still unknown, there are two grades of glioma: low-grade glioma (LGG) and high-grade glioma (HGG). The latter is the most aggressive and very infiltrative because it quickly spreads into other parts of the brain; thus, then early detection of the tumor is very crucial because it enhances the rate of survival and facilitates the therapy phase. Medical imaging analysis comes to help patients and saves people’s lives by diagnosis using new safety technology, such as positron emission tomography (PET), computed tomography (CT), and magnetic resonance imaging (MRI). T1-weighted, T2-weighted, T1-weighted with contrast enhancement (T1ce), and fluid-attenuated inversion recovery (FLAIR) are the four modalities of MRI images, as seen in Figure 1, and each one is in 2D slices form and puts all the slices together produce a 3D form of the brain. Utilization of multiple modalities and sequences to segment the brain tumor can improve results and provide complementary features on regions of different sub-gliomas. Semi-automatic and automatic approaches have been proposed in the brain tumor segmentation area and the automatic one showed its performance and a high potential for more accurate and reliable results. Therefore, numerous studies have proved to detect and segment different types of brain tumors without using ground truth labels. Based on machine learning (ML) algorithms, K-means clustering is frequently used to separate an interest region from an image. K-means has undergone thorough testing in the segmentation of brain tumors and has demonstrated acceptable accuracy [1,2]. Almahfud et al. [3] proposed a combination of K-Means and Fuzzy C-Means. They applied this combination to make the image more visible. Then, they mapped it, applied a median filter, and used morphological area selection to eliminate small pixels and detect the location of the tumor [4]. A genetic algorithm is relied on to create a new technique of segmentation discrete wavelet transform and a fitness function variance as an objective function. This method obtained a high performance in terms of accuracy. For supervised approaches with ML, Cui et al. [5] extracted features using an intensity texture after image registration in the preprocessing phase. Multi-kernel support vector machine (SVM) is employed as a classifier and a region growing to postprocess the results. Chen et al. [6] used N4ITK, histogram matching, and simple linear iterative clustering for preprocessing, gray statistical and gray-level co-occurrence matrix for feature extracting, and SVM as a classifier [7,8]. They employed other classifiers, random forest, morphological techniques, and some filtering methods in postprocessing to segment tumors. Therefore, the first used noise removal in preprocessing and the first higher-order plus texture as a vector of features, and the second was based on histogram enhancement and Gabor wavelet in addition to intensity in preprocessing and feature extracting, respectively. The intensity non-uniformity inMRI imaging makes the feature’s extracted phase more complex inML methods, and the amount of this type of data affects the performance of most ML algorithms and limits their results. Deep learning comes to solve this type of limitation and it has proven its performance in medical imaging analysis and retrieval [9,10] in general, and in medical imaging segmentation specifically. Convolution neural networks (CNNs) and the encoder–decoder with skip connection is the first and themost used in this area. Therefore, Pereira et al. [11] employed a custom CNN followed by bias field correction, intensity, patch normalization, and data augmentation. Themethods [12,13] integrated a full CNN to segment different regions of the tumor, and then [12] FCNN was combined with conditional random forest (CRF). On the other hand [13], a cascade of FCNN is proposed to decompose the multi-classes segmentation problem into three binary segmentations. in this area. Therefore, Pereira et al. [11] employed a custom CNN followed by bias field correction, intensity, patch normalization, and data augmentation. The methods integrated a full CNN to segment different regions of the tumor, and then FCNN was combined with conditional random forest (CRF). On the other hand, a cascade of FCNN is proposed to decompose the multi-classes segmentation problem into three binary segmentations. used the features extracted from the last convolution layer of CNN-proposed model, calculated a gradient of those features, stocked the mean and the max of each one in two vectors, and multiplied them by the features component by component. Finally, a thresholding and morphological process to postprocess the whole tumor was used. This method did not use the mask, but it obtained a high performance in terms of dice coefficient similarity. On the other hand, U-Net-like architectures showed their majority and success. U-Net is a symmetric fully convolutional network proposed by Ronneberger et al. [15] with a decoder path to ensure precise position and an encoder path to capture context information. U-Net is still used as a reference in both 2D and 3D brain tumor segmentation, and several methods were inspired by making adjustments to the encoder, skip connection, or decoder parts. Liu et al. proposed a novel cascadeU-Net inwhich each basic block is designed as a residual one to overcome the vanishing gradient problem. Additionally, they designed some skip connections to enhance the features transmitted between the encoder and decoder. introduced a hybrid two-track U-Net. They merged two tracks, and each one employs a different kernel and number of layers to obtain a final segmentation result. The architecture employed batch normalization and it chose Leaky ReLU as an activation function. Recently, U-Net has been combined with transfer learning in the latest research to solve a complex limitation of contraction path in U-Net. A lot of time is spent on its execution using a pre-trained model and obtaining more significant features. Moreover, U-Net-VGG16 [18] was one of those contributions. Then, they replaced the encoder path with VGGNet [19]. The same idea was applied to several hybrid architectures replacing VGG-Net with other CNN architectures, such as LeNet [20], AlexNet [21], MobileNet [22], and ResNet [23]. Meanwhile, these methods still raise challenges to learning global semantic information, which is critical for segmentation tasks; therefore, the attention mechanism was introduced to overcome these challenges.

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The article discusses brain tumors, which account for 85-90% of primary central nervous system tumors. It discusses the different types and grades of gliomas and the importance of early detection. Medical imaging analysis is important for diagnosis and MRI is the most commonly used modality. Both semi-automatic and automatic approaches have been proposed using machine learning algorithms. K-means clustering has been used to segment brain tumors with acceptable accuracy. Deep learning has been successful in medical imaging analysis and segmentation, with convolutional neural networks (CNNs) and U-Net architectures being the most used. Hybrid architectures have been developed that replace the encoder path with other CNN architectures and use the attention mechanism to improve segmentation accuracy.

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Several studies have been done to extract features and use different classifiers for segmentation. The intensity non-uniformity in MRI imaging makes the feature extraction phase more complex in ML methods. Deep learning has proven to be successful in overcoming these limitations and has shown remarkable performance in medical imaging analysis and segmentation. U-Net has been used as a reference in both 2D and 3D brain tumor segmentation, and different adjustments were made to its encoder, skip connection or decoder parts in several hybrid architectures to improve performance. These methods still face challenges in learning global semantic information critical for segmentation tasks, which are being addressed by introducing the attention mechanism. Overall, the article emphasizes the importance of early detection and the use of medical imaging analysis and machine learning techniques for accurate and reliable brain tumor segmentation.

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The article highlights the significance of brain tumor segmentation by medical imaging analysis for effective diagnosis and treatment. It discusses different approaches involving machine learning algorithms, especially deep learning, and various architectures for brain tumor segmentation. The article emphasizes the importance of early diagnosis and provides details of different modalities used for medical imaging like MRI, CT, and PET.

The study also discusses challenges associated with brain tumor segmentation processes, such as intensity non-uniformity, and explains how they are currently being addressed by introducing new technologies and techniques like deep learning and attention mechanisms. The examples of various studies and their procedures illustrate different approaches that have been successful in developing accurate and reliable segmentation in brain tumor analysis.

Finally, the paper reveals that brain tumors are still one of the leading causes of disease-related deaths, with the numbers increasing worldwide every year. Medical researchers, healthcare practitioners, and policymakers must prioritize the development and optimization of effective brain tumor segmentation techniques to identify patients earlier, provide more timely and effective treatments, and, ultimately, save lives.

summarize this text

: Fusing CNN-based methods, U-Net architectures and attention mechanisms can allow for extracting more precise dense feature information in the downsampling, and they can effectively recover spatial information and position details in the upsampling path. In this context, Zhang et al. [24] proposed Attention Gate ResU-Net for automatic MRI brain tumor segmentation. They employed a residual block and an attention gate with a single U-Net architecture added into the skip connection part. On the other hand, Wu et al. [25] developed a new method based on generative adversarial network (GAN) named symmetric driven GAN. The method was trained and learned a non-linear mapping betwixt the left and right brain images, along with the variability of the brains. Another method that relies on GAN has been proposed by Dey et al. [26]. They introduced a framework named the Adversarial-based Selective Network ASC Net that aims to decompose an image into two selective cuts based on a reference image distribution. One cut will fall into the reference distribution, while other image content outside of the reference image distribution will group into the other cut. These two cuts reconstruct the original input image semantically and apply simple thresholding to regroup normal and abnormal regions. In this paper, we developed a new architecture belonging to U-Net-like ones. The architecture consists of two parts: an encoder and a decoder. The first part used three different pre-trained models of CNNs to create a multiple encoder in order to extract more local features. We introduced the features extracted from each encoder as input into a bidirectional feature pyramid network (Bi-FPN) to enrich them, and a concatenation has been affected into those Bi-FPN outputs to obtain overall specific features. In the second part, we upsampled the encoded feature map based on the attention mechanism that allows us to better preserve fine details and ignore irrelevant information about those features and to produce a segmentation mask that is the same size as the input image. Section 2 will describe the materials and methods and Section 3 will be devoted to representing the results. Then, Section 4 is mainly concerned with discussion and conclusions.

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The text discusses various methods for automatic MRI brain tumor segmentation using CNN-based methods, U-Net architectures, and attention mechanisms. Several studies have used generative adversarial networks (GANs) to improve segmentation accuracy. In this paper, a new architecture belonging to U-Net-like ones was developed with three pre-trained models of CNNs as encoders. The features extracted from each encoder were enriched by concatenating Bi-FPN outputs to obtain overall specific features. The second part involved up-sampling the encoded feature map based on the attention mechanism and producing a segmentation mask. The materials and methods, results, discussion and conclusions are discussed in further sections of the paper.

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The authors propose a new architecture that leverages pre-trained models of CNNs to extract more local features, concatenated utilizing a Bidirectional Feature Pyramid Network (Bi-FPN). They then use the attention mechanism to upsample the feature map, maintaining fine details while ignoring irrelevant information. This architecture intends to provide an efficient solution for accurate and detailed segmentation of brain tumors.

Overall, the text highlights the potential of various deep learning techniques in the field of medical image analysis and brain tumor segmentation. Different methods like GAN and adversarial-based selective network have been proposed and achieved promising results. The authors' proposed architecture combines different models to extract fine details and produce accurate segmentation masks. The article demonstrates the importance of using advanced techniques in medical image analysis and shows the potential for deep learning approaches in improving the accuracy and efficiency of brain tumor segmentation.