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# A survey of deep learning methods for MRI brain tumor image segmentation

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***Abstract:*** **Automatic segmentation of MRI brain tumors based on deep learning can automatically extract more expressive and discriminative brain image features. In view of the application value of deep learning in brain tumor segmentation, this paper systematically reviews the deep learning methods for MRI brain tumor segmentation. Firstly, the research status and significance of brain tumor segmentation methods based on deep learning are analyzed in detail. The deep learning segmentation algorithm performs well, but there are also problems such as the poor ability to capture long-distance dependence and less labeled brain image data. This paper summarizes the principles and advantages of these algorithms and performs some algorithms. Finally, the future of MRI brain tumor segmentation methods is based on deep learning prospects.**

***Keywords: MRI brain tumor imaging, segme-ntation, deep learning***

## I. INTRODUCTION

The brain tumor is one of the most common malignant tumors, which can be divided into primary and secondary[1]. Primary tumor cells are derived from the brain tissue itself and grow in the brain; secondary tumor cells spread from other tissues. Gliomas originating from glial cells are the most common and have the highest mortality rate. Gliomas are divided into low-grade gliomas (LGG) and high-grade gliomas (HGG). LGG is a benign tumor and HGG is a malignant tumor. At present[2], brain tumors are diagnosed by medical imaging. Early diagnosis can improve the survival rate of patients. Among many medical imaging methods, magnetic resonance imaging (MRI) technology is widely used in the detection and diagnosis of brain tumors.

Magnetic resonance imaging (MRI) is a non-invasive imaging technology with no bone artifacts, multi-parameter and multi-angle imaging[3]. Compared with computed tomography (CT), MRI has better contrast to soft tissue and no radiation damage. Various imaging parameters can provide rich diagnostic information and are widely used in the diagnosis and detection of brain tumors. Since 2012, the Medical Image Computing and Computer-Aided Intervention Conference (MICCAI) has held the Brain Tumor Segmentation Competition (BraTS) every year and provided a multimodal MRI brain tumor dataset[4]. The datum contains four modalities (T1, T2, T1ce, FLAIR)[5]. MRI produces a large amount of brain image data in the clinical application of brain tumor diagnosis. It is impossible for doctors to manually annotate and segment all image data in time, and manual segmentation of brain tumors depends entirely on the doctor's personal experience. So, how to accurately and efficiently automatic segmentation of brain tumors has become a research hotspot.

This paper attempts to make a comprehensive and detailed review of the existing MRI image brain tumor segmentation methods based on deep learning, summarize and analyze the research progress, advantages and disadvantages, and result evaluation of such methods, and make a preliminary prospect for the future of MRI brain tumor segmentation.

## II. BRAIN TUMOR SEGMENTATION METHOD BASED ON CONVOLUTIONAL NEURAL NETWORK

The brain tumor segmentation method based on convolutional neural network (CNN)[6] integrates three structural ideas (local receptive field, weight sharing, and spatial subsampling)[7], which can achieve a certain degree of displacement and deformation stability[8]. Therefore, no matter whether the target flips, moves, or scales in the image, it can be identified and extracted, which is very beneficial to image segmentation.

### *A. 2D Convolutional Neural Network*

Havaei et al.[9]constructed a cascaded CNN network to capture the missing information in the network, which has good generalization. In BraTS2015, DSC coefficients of complete tumor region, tumor core region, and enhanced tumor region segmentation are 0.79, 0.58, and 0.69. But the model does not pay attention to spatial information, resulting in poor network segmentation performance. Lyksborg et al.[10] integrated multiple 2D-CNN networks for volume segmentation of MRI brain tumor images, which performed better than a single 2D-CNN network and were outstanding in BraTS2014.

Although the segmentation effect of 2D-CNN is good, due to the different attention information of researchers on brain tumors, many spatial information factors will be ignored, which limits the development of brain tumor segmentation. Therefore, most researchers began to shift to the 3D direction.

### *B. 3D Convolutional Neural Network*

3D-CNN can preserve the spatial information of MRI brain tumor images and improve the segmentation performance. Kamnitsas et al.[11] proposed a dual-channel 3D-CNN model that simultaneously processes input image information from multiple angles. It effectively combines contextual information. DSC coefficients trained in BraTS2015 are 0.90,0.76, and 0.73, however, processing multi-scale 3D images at the same time will make efficiency low. The model of Kamnitsas et al. was improved by Casamitjana et al.[12], using the same size input in the dual path architecture, and adding fine features and coarse features. DSC coefficients trained in BraTS2015 were 0.92, 0.84, and 0.77. 3D-CNN retains more image data information than 2D-CNN, but it is computationally intensive and difficult to implement the model.

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Table 1 list the segmentation performance of some CNN models in the BraTS dataset. DSC_WT is the DSC coefficient of the complete tumor region. DSC_TC represents the DSC coefficient of the core tumor region, and DSC _ET represents the DSC coefficient of the enhanced tumor region. It can show in table 1 that the segmentation performance of the 3D-CNN model is generally better than that of the 2D-CNN model.

Table 1. DSC Coefficients of Partial 2D or 3D CNN Models in MRI Brain Tumor Segmentation

| Method | Category | Dataset | DSC_WT | DSC_TC | DSC_ET |
|---|---|---|---|---|---|
| Havaei | 2D | BraTS 2015 | 0.79 | 0.58 | 0.69 |
| Pereia[13] | 2D | BraTS 2015 | 0.79 | 0.65 | 0.75 |
| Kamnitsas | 3D | BraTS 2015 | 0.90 | 0.76 | 0.73 |
| Casamitjana | 3D | BraTS 2015 | 0.92 | 0.84 | 0.77 |
| Qamar[14] | 3D | BraTS 2018 | 0.87 | 0.81 | 0.84 |
| Urban[15] | 3D | BraTS 2013 | 0.86 | 0.75 | 0.73 |
| Feng Bowen[16] | 3D | BraTS 2018 | 0.90 | 0.73 | 0.71 |

## III. BRAIN TUMOR SEGMENTATION METHOD BASED ON FULLY CONVOLUTIONAL NEURAL NETWORK

Fully Convolutional Networks (FCN) are formed based on VGG16. It is first proposed by Long et al[17]. It can segment images of any size and replace the former fully connected layer of CNN with a convolutional layer. It is an end-to-end semantic segmentation network. Figure 1 is based on the maximum convolutional network MRI brain tumor segmentation architecture map.

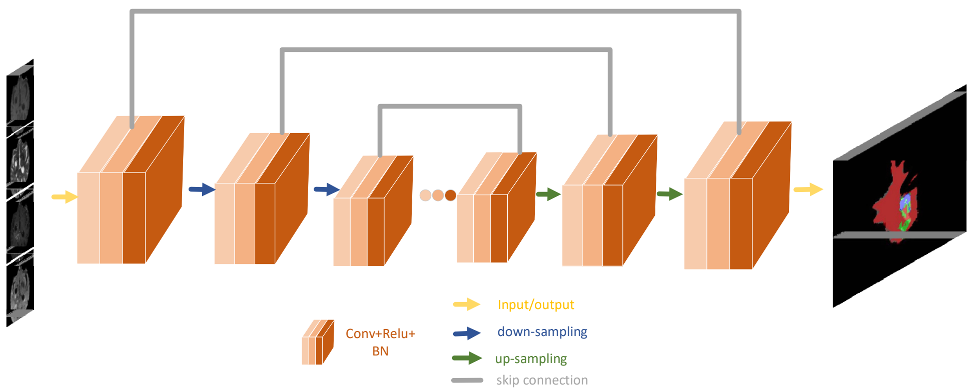


Figure 1. MRI Brain Tumor Segmentation Network Architecture Based on Fully Convolutional Network

Shen et al.[18] first applied FCN to multimodal brain tumor image segmentation. DSC coefficients of the proposed model trained in BraTS2013 are 0.86, 0.73, and 0.73. To improve the problem of unclear tumor edge segmentation, Shen et al.[19] improved the original model and introduced a tree structure. DSC coefficients trained in BraTS2013 were 0.87, 0.82 and 0.75. FCN has attracted the attention of researchers since it proposes. Various network models based on FCN have also appeared one after another. The most widely used one is the U-Net model proposed by Ronneberger et al.[20] U-Net was originally used in the field of biomedical cell segmentation, named for its network structure similar to ' U ', and the network body consists of an encoder-decoder, as shown in Figure 2, where Conv represents convolution for feature extraction; copy & concat represents skip connection for feature fusion; max Pool represents maximum pooling for reducing dimensions; up-Conv represents up-sampling for restoring dimensions. U-Net adds multiple skip connections based on FCN to fuse high-level and low-level features, which enables the network to complete large-scale image segmentation. Because of its simple operation and good segmentation effect in the case of small data volume, it quickly becomes a mainstream method in medical image segmentation.

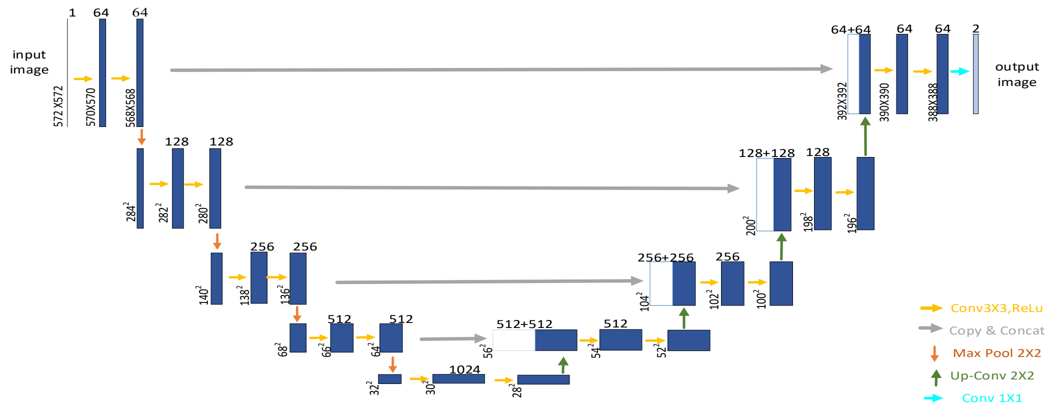


Figure 2. U-Net network structure

Dong et al.[21] used 2D U-Net for brain tumor segmentation earlier. He proposed an automatic brain tumor segmentation model, and DSC coefficients trained in BraTS2018 were 0.88, 0.87, and 0.81. To improve the performance of network segmentation, researchers have combined some advanced methods with U-Net. Shaikh et al.[22] combined dense connection blocks with 2D U-Net and introduced conditional random fields for post-processing. DSC coefficients trained in BraTS2017 were 0.83, 0.65, and 0.65. Recently, Xia Feng et al.[23] proposed CSPU-Net network model, adding a cross-stage local network to the up-down sampling structure of U-Net to extract image features, and combining dice loss and weighted cross entropy to solve the problem of unbalanced training samples. DSC coefficients trained in BraTS2019 were 0.87, 0.77 and 0.70.

2D U-Net has low memory requirements and high computational efficiency, but it lacks attention to spatial information. Therefore, researchers began to use 3D convolution to design brain tumor segmentation networks. The 3D U-Net model proposed by Menze et al.[24] in the BraTS2017 challenge is one of the classic models. DSC coefficients of the model trained in BraTS2017 are 0.88, 0.76 and 0.72. In the brain tumor segmentation model based on U-Net, nnU-Net has been popular in recent years. NNU-Net is a fully automatic segmentation network proposed by Fabian et al[25]. It can be automatically configured, including preprocessing, network architecture, training, and post-processing of any new task. The DSC coefficient trained in BraTS2020 is 0.89, 0.85, and 0.82. Huan et al.[26] doubled the number of filters in the nnU-Net encoder, kept the number of filters in the decoder unchanged, asymmetrically expanded the network, and used axial attention in the encoder to improve the neural network segmentation performance further.

Table 2. Evaluation results of MRI brain tumor segmentation method based on FCN

| Method | Category | Dataset | DSC_WT | DSC_TC | DSC_ET |
|---|---|---|---|---|---|
| Shen | 2D FCN | BraTS 2013 | 0.86 | 0.73 | 0.73 |
| Puch[27] | 3D FCN | BraTS 2018 | 0.90 | 0.80 | 0.75 |
| Dong | 2D U-Net | BraTS 2018 | 0.88 | 0.87 | 0.81 |
| Shaikh | 2D U-Net | BraTS 2017 | 0.83 | 0.65 | 0.65 |
| Ai Lingmei[28] | 2D U-Net | BraTS 2018 | 0.90 | 0.79 | 0.78 |
| Xia Feng | 2D U-Net | BraTS 2019 | 0.87 | 0.77 | 0.70 |
| Menze | 3D U-Net | BraTS 2017 | 0.88 | 0.76 | 0.72 |
| He Chengen[29] | 3D U-Net | BraTS 2017 | 0.90 | 0.80 | 0.77 |
| Feng[30] | 3D U-Net | BraTS 2018 | 0.91 | 0.84 | 0.79 |
| YU Li[31] | 3D U-Net | BraTS 2020 | 0.90 | 0.85 | 0.79 |
| Fabian[32] | 3D U-Net | BraTS 2020 | 0.89 | 0.85 | 0.82 |
| Huang | 3D U-Net | BraTS 2021 | 0.94 | 0.92 | 0.88 |

Table 2 lists the performance of some FCNs in the BraTS dataset. It can be seen from Table 2 that this method performs better in the complete tumor part than in the tumor core and enhanced tumor. The main reason is that the tumor core and enhanced tumor account for too small a proportion of the entire image and lose information during the down-sampling process. In addition, FCN combined with other technologies, such as conditional random fields (CRF), dilated convolution, etc., can improve segmentation accuracy.

## IV. BRAIN TUMOR SEGMENTATION METHOD BASED ON GENERATIVE ADVERSARIAL NETWORK

The generative adversarial network (GAN) proposed by Goodfellow et al.[33] is a representative of unsupervised learning. The GAN network is composed of a generator (G), discriminator (D), and real data X. The generator can produce more realistic objects (such as human and animal photos; discriminators are used to distinguish between generated objects and real objects. When training the network, the generator and the discriminator overlap each other and are continually optimized for optimal results in opposing situations.

Due to the disappearance of the gradient in the process of adversarial optimization, it is easily affected by network collapse and instability. Nevertheless, the GAN network still attracts much attention and is applied to the field of MRI brain tumor image segmentation.

Luc et al.[34] first applied the GAN network to the field of segmentation. After that, Rezaei et al.[35] proposed voxel-GAN network to alleviate the class imbalance problem in brain tumor segmentation. DSC coefficients trained in BraTS 2018 were 0.84, 0.79 and 0.63. To solve the problem of information loss in the network model, Zhang Chao et al.[36] proposed a two-stage generative adversarial network (ToStaGAN) based on parallel multi-scale from the perspectives of phased processing and multi-scale features. DSC coefficients trained in BraTS 2015 were 0.85, 0.71 and 0.62.

The brain tumor segmentation method is based on the GAN network and uses semi-supervised learning to enhance and expand the data in real-time when training the model, which alleviates the imbalance of MRI brain tumor image data samples to a certain extent. Table 3 lists the segmentation results of some tumor segmentation methods based on the GAN network in the BraTS dataset.

Table 3. Performance of MRI Brain Tumor Segmentation Based on GAN Network

| Method | Dataset | DSC_WT | DSC_TC | DSC_ET |
|---|---|---|---|---|
| Xue[37] | BraTS 2015 | 0.85 | 0.70 | 0.66 |
| Rezaei[35] | BraTS 2018 | 0.84 | 0.79 | 0.63 |
| Zhang[36] | BraTS 2015 | 0.85 | 0.71 | 0.62 |

## V. BRAIN TUMOR SEGMENTATION METHOD BASED ON TRANSFORMER

Ashish et al.[38] proposed a completely attention-based sequence transduction model, which replaces the recursive layer of the encoder-decoder architecture with multi-head self-attention, called Transformer. Since the transformer performs better than most traditional models in the field of natural language processing, some researchers have begun to use it for medical image processing. Joya et al.[39] proposed a gated axial attention model (Medical Transformer). This model introduces additional control mechanisms into the self-attention module to expand the network structure and uses a local-global training strategy to improve the performance of the model. It is one of the early applications of transformers in medical image processing. Wang et al.[40] proposed a new structure (TransBTS), the encoder uses 3D CNN to extract spatial feature maps; the decoder uses the features embedded in the transformer and performs progressive up-sampling to predict the detailed segmentation map. DSC coefficients trained in BraTS2019 are 0.90, 0.82, and 0.79.

When applying a transformer to the field of medical image volume segmentation, how to design computationally efficient Transformer architecture is a difficult problem. To this end, Himashi et al.[41] proposed the VT-UNet network. The model has a U-shaped encoding-decoding design. The encoder has two continuous self-attention layers to encode local and global information simultaneously. The decoder has a self-attention layer and a cross-attention block. DSC coefficients trained in BraTS2021 are 0.91, 0.87, and 0.86. Zhou et al.[42] proposed the nnFormer model, introduced a self-attention mechanism based on local and global volumes to learn the volume representation and used jump attention to replace the additive operation of jump connection in the U-Net architecture. The network structure is shown in Figure 3. DSC coefficients trained in the BraTS2016 and BraTS2017 mixed data sets are 0.91, 0.86, and 0.82.

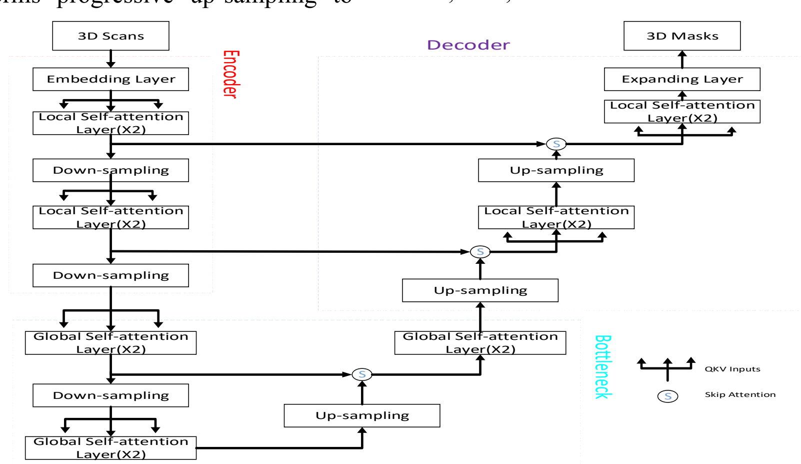


Figure 3. nnFormer network structure diagram

Table 4 lists the performance of some MRI brain tumor segmentation methods based on the transformer in the BraTS series data set. Thanks to its self-attention module and the ability to obtain context information, the transformer can effectively alleviate the problems of target shape and size differences in MRI brain tumor image segmentation tasks. But it needs a large enough number of data sets to give full play to its advantages. With the help of U-Net, we can better use the sample information to extract multi-scale local spatial features, balance the global and local information of the model, and further improve the performance of the model.

Table 4. MRI brain tumor image segmentation performance based on Transformer

| Author | Method | Dataset | DSC_WT | DSC_TC | DSC_ET |
|---|---|---|---|---|---|
| Wang | TransBTS | BraTS 2019 | 0.90 | 0.82 | 0.79 |
| Himashi | VT-UNet | BraTS 2021 | 0.91 | 0.87 | 0.86 |
| Zhou | nnFormer | BraTS 2016&2017 | 0.91 | 0.86 | 0.82 |
| Ali[43] | UNETR | - | 0.79 | 0.76 | 0.59 |

Note : - Indicates no data

## VI. CONCLUSION AND FORESIGHT

In recent years, the prevalence of brain tumors has been increasing, and manual segmentation by doctors alone has not kept up with clinical needs. Therefore, the automatic segmentation of brain tumors has become a research hotspot. The segmentation method based on deep learning has greatly improved the segmentation performance compared with the traditional method, but it cannot achieve clinical practical application and needs further exploration.

1）Attention can improve the model's ability to express the features of the input brain image, while the transformer has a self-attention module, which is used to form a network without adding other attention, and it can capture global context information to further improve the model performance. Studying the combination of Transformer and other segmentation networks is an exploratory direction.

2）At present, the large-scale MRI brain tumor data labeled by experts are very scarce. Semi-supervised or unsupervised learning can be performed in combination with tumor information (shape, location, etc.) to expand the data in real-time and enrich the data set to improve the segmentation performance of the model.

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