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Deep Learning Segmentation Approach For Brain Tumor Detection Using MRI

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Abstract: Brain tumor is the linear growth of abnormal or cancerous cells around the brain or inside the brain. Based on the origination of tumor inside the brain, the glioma is categorized into two different categories as: primary tumor and secondary tumor. The primary tumor can be benign or malignant, which does not spread to other location of human body.However, the brain tumor is categorized as segmentation and classification-based methods. This paper deals with Based on the functional features of brain tumor, the segmentation and the classification methods are categorized. The proposed approach here the brain tumor segmentation methods used to segment the core region of tumor is elaborated as Deep learning-based segmentation methods. As the results the segmentation accuracy obtained by the deepjoint segmentation with population size 10, deepjoint segmentation with population size 20, deepjoint segmentation with population size 30, deepjoint segmentation with population size 40, and deepjoint segmentation with population size 50 is 75.78%, 75.79%, 93.48%, 93.50%, and 93.52%, respectively.

Keywords: Brain Tumor; deepjoint segmentation; MRI Image.

1. Introduction

Brain tumor is the linear growth of abnormal or cancerous cells around the brain or inside the brain. Based on the origination of tumor inside the brain, the glioma is categorized into two different categories as: primary tumor and secondary tumor. The primary tumor can be benign or malignant, which does not spread to other location of human body. However, the secondary tumors are considered as malignant. Gliomas and meningiomas are the low-grade tumors and are categorized as benign tumor. The astrocytoma and glioblastoma are the high-grade tumors and are classified as malignant tumor. The term brain or glioma tumor refers to the collection of neoplasms, where each has its own prognosis, treatment, and biology. Hence, these tumors are specified as intracranial neoplasms as some of these may not arise from the brain tissues. Gliomas are the frequent brain tumor that affects the dults by originating from the glial cells and infiltrated to the surrounded tissues. In general, brain tumor is a collection of abnormal cells that linearly grows inside the brain or nearby the brain structure. Due to the varying shape, size and location of tumor, detecting the brain tumor is challenging task in the medical sector.

2. Categorization And Description Of Works

In this section, the categorization and description of brain tumor is explained. However, the brain tumor is categorized as segmentation and classification-based methods. Figure 1 shows the categorization of brain tumor techniques Based on the functional features of brain tumor, the segmentation and the classification methods are categorized as follows:

1) Deep learning methods
2) Intensity-based methods
3) Hybrid methods
4) Deformable model-based methods

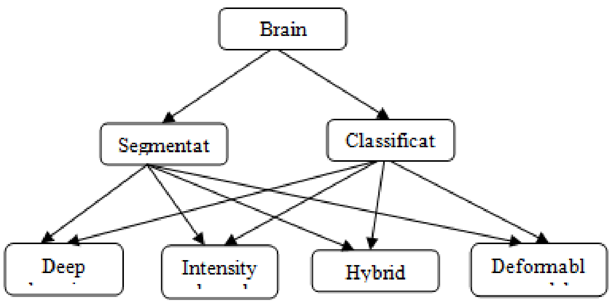

Figure 1 Categorization and description of brain tumor techniques

2.1 Brain tumor segmentation methods

The brain tumor segmentation methods used to segment the core region of tumor is elaborated in this section.

2.1.1 Deep learning-based segmentation methods

The deep learning-based brain tumor segmentation methods used to model the pathological brains and generating the pathological brain atlases are discussed in this section.

Pereira *et al.* (2016) modeled a CNN classifier for automatic tumor segmentation using MR images. Gliomas were the aggressive and most common tumor that leads to death with highest grade. To plan the treatment strategy at early stage was the key component to increase the life of human. MRI was the highly significant method used to access the tumor region, but the data generated by the MRI prevented to perform manual segmentation at reasonable time. However, the large structural and spatial variability of brain tumor made the segmentation process more complex. It also used the intensity normalization and data augmentation model to achieve tumor segmentation in the MRI image. The detection rate of this model was very less.

Hussain *et al.*(2018) introduced a Deep CNN classifier to segment the brain tumor automatically. It used the inception module along with the patch-based model to extract the co-centric phases with different sizes by training the network classifier. Here, the linear nexus architecture was modeled using the recent network classifiers, like non-linear activation, inception module, batch normalization, and dropout. Due to the dropout regularize with the scarcity of data, the over fitting problem was reduced. Deep CNN used the normalized images and allocated the output label to the patch of central pixel.

Chen *et al.*(2019) introduced a Deep Convolutional Symmetric NN (DCSNN) for segmenting the brain tumor effectively. Glioma tumor have high mortality rate and surgery is the only way to perform the treatment planning. MRI was helpful in accessing the glioma and making the successful treatment in the clinical strategy. The major key role in the treatment and diagnosis planning was to accurately segment the glioma tumor. Due to the structural and spatial variability between the brain tumor brings complex issue in automatically segmenting the MR images.

Yang *et al.*(2019) introduced a Random Forest (RF) and small kernels two-path CNN (SK-TPCNN) for automatically segmenting the brain tumor. To segment the glioma tumor from MRI was a key role in treatment planning, and early diagnosis. Due to the significant diversity in glioma structure, the accuracy of tumor segmentation resulted poor. Here, the optimization capability and the ability of feature extraction were joined together to perform effective tumor segmentation. The large convolutional kernels and the small convolutional kernels of SK-TPCNN structure were combined to reduce the over fitting and to increase the nonlinear mapping such that the features with the multiformity rate was also increased.

Li *et al.*(2019) developed an end-to-end tumor segmentation method based on convolutional network using the image slices at both the testing and training phase. This method was more effective and faster than the patch-wise techniques. An enhanced U-net architecture was introduced with the innovative-up skip connection for increasing the inception modules and information flow to determine the richer representations. It utilized the cascade U-net for sequentially segmenting the tumor sub-regions. Moreover, the cascaded training model was adopted to enhance the performance of segmentation for small glioma tumor region with the transfer knowledge. Accurate tumor segmentation using MRI image was an active research in the medical analysis system as it offered doctors with the reliable and meaningful quantitative data in monitoring and diagnosing the neurological diseases.

Mlynarski*et al.* (2019) developed a CNN-based segmentation method to enhance the training phase of tumor segmentation. It used the hierarchical decision model using various segmentation modules to overcome the limitations of network architectures. The major role of this model was to increase the robustness and performance of the CNN-based system. The multi-class segmentation generated using the adopted method was merged with the voting strategy for segmenting the tissue structure. It attained better performance by producing enhanced dice scores and segmentation accuracy rate. However, this model significantly increased the memory load and computation overhead.

Zhao *et al.*(2018) introduced a deep learning-based segmentation method with the integration of CRF and Fully Convolutional Neural Networks (FCNN) to generate the segmented results with the spatial consistency and appearance. However, the deal learning classifier was trained using the image slices and image patches. Moreover, it trained the CRF and CNN based on image patches and generated the sagittal, coronal, and axial views, respectively. Here, the image patches were sampled using training dataset and the image patches belongs to the same class, which was selected as the training patches that further helped to solve the data imbalance problem. The image slices were combined together to perform the brain segmentation through the voting-based fusion model. Figure 2. Portrays the Basic architecture of brain tumor segmentation.

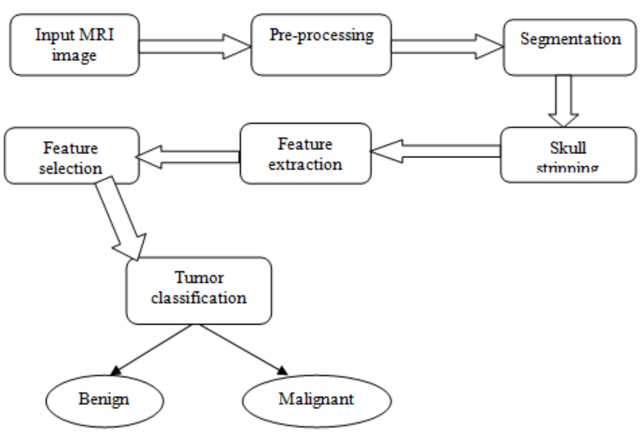

Figure 2. Basic architecture of brain tumor segmentation

3 Performance Analysis Of The Proposed Methodology

The performance analysis made using the deepjoint segmentation in terms of the metrics, such as, segmentation accuracy is discussed in this section.

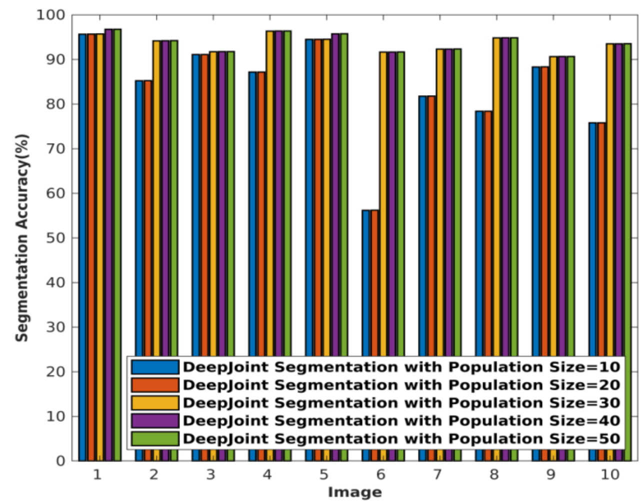

Figure 3 Performance analysis of the proposed deepjoint segmentation in terms of segmentation accuracy using HGG dataset

When image=1, the segmentation accuracy obtained by the deepjoint segmentation with population size 10, deepjoint segmentation with population size 20, deepjoint segmentation with population size 30, deepjoint segmentation with population size 40, and deepjoint segmentation with population size 50 is 95.66%, 95.68%, 95.70%, 96.75%, and 96.77%, respectively.

When image=4, the segmentation accuracy obtained by the deepjoint segmentation with population size 10, deepjoint segmentation with population size 20, deepjoint segmentation with population size 30, deepjoint segmentation with population size 40, and deepjoint segmentation with population size 50 is 87.16%, 87.18%, 96.34%, 96.36%, and 96.38%, respectively.

When image=6, the segmentation accuracy obtained by the deepjoint segmentation with population size 10, deepjoint segmentation with population size 20, deepjoint segmentation with population size 30, deepjoint segmentation with population size 40, and deepjoint segmentation with population size 50 is 56.18%, 56.19%, 91.63%, 91.65%, and 91.67%, respectively.

When image=10, the segmentation accuracy obtained by the deepjoint segmentation with population size 10, deepjoint segmentation with population size 20, deepjoint segmentation with population size 30, deepjoint segmentation with population size 40, and deepjoint segmentation with population size 50 is 75.78%, 75.79%, 93.48%, 93.50%, and 93.52%, respectively.

4 Conclusion

This paper deals with Based on the functional features of brain tumor, the segmentation and the classification methods are categorized. The proposed approach here the brain tumor segmentation methods used to segment the core region of tumor is elaborated as Deep learning-based segmentation methods. As the results the segmentation accuracy obtained by the deepjoint segmentation with population size 10, deepjoint segmentation with population size 20, deepjoint segmentation with population size 30, deepjoint segmentation with population size 40, and deepjoint segmentation with population size 50 is 75.78%, 75.79%, 93.48%, 93.50%, and 93.52%, respectively.75.78%, 75.79%, 93.48%, 93.50%, and 93.52%, respectively.

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