Brain Tumor Segmentation using Fully Connected Convolutional Neural Network (FCNN)

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Abstract - *In the neurological department segmenting a brain cancer is a cruel work for the neurologist to manually segment the brain cancer. Brain cancer segmentation is a difficult task in identifying cancer in a person. It involves a plan of treatment, to evaluate the outcome of a treatment[5]. In this method, we use patches of a brain MR image to detect the brain cancer of a patient[6]. We developed a model that consists of both fully connected convolution neural networks and cacaded conditional random fields. We use a deep neural network to train 2D images and four different modalities of the brain image. And then fine segmenting the FCNN and Cascaded CRF[8] using 2D images[5].*

Key Words: *Brain Cancer Segmentation, Fully Connected Convolution Neural Network[4], cascaded Conditional Random Fields[4], Deep learning.*

1. INTRODUCTION

Brain cancer is an irregular growth of cells inside the brain. This growth of the cells may be benign or malignant. A benign brain cancer develops gradually, has definite limits, and unusually spreads[4]. Although its cells are not cancerous, harmless brain cancers can be life-threatening if found in an essential region. A malignant brain cancer spreads quickly, has unusual limits, and spreads to nearby brain areas[6]. Although they are often called brain cancer, malignant brain cancers do not fit the definition of cancer because they do not spread to organs +outside the brain Considering the manual segmentation of brain cancer is laborious, an immense effort has been dedicated to the development of semi-automatic or automatic brain cancer segmentation methods[5].

Most of the present brain cancer segmentation researches are converging on gliomas that are the most common brain cancers in adults and can be estimated by Magnetic Resonance Imaging (MRI) scan with multiple progressions, such as T2-weighted, Fluid Attenuated inversion recovery (Flair), T1-weighted, T1-weighted contrast-enhanced, and T2-weighted[4]. The segmentation of gliomas based on MRI scan results is disputing for gliomas may have the identical condition as gliosis and stroke in MRI scan data, gliomas may issue in any location of the brain with a different form, condition, and measurement, gliomas attack the neighboring brain cancer slightly than removing them, making obscure boundaries, strength in+homogeneity of MRI scan data additional advances the problem[4].

The existing automatic and semi-automatic brain cancer segmentation methods can be broadly classified as either generative representation based or perceptive design methods. The generative paradigm based brain cancer segmentation techniques typically need past data, which could be obtained by probabilistic picture atlases. Based on probabilistic image atlases, the brain cancer segmentation problem can be represented as an outlier exposure difficulty[4]. Approaching the opposite side, the intelligent design systems answer the brain cancer segmentation problem in a pattern classification setting.

Further, newly, deep learning methods have been utilized in brain cancer segmentation investigations regarding their progress toward common image interpretation fields, such as image classification, object detection, and semantic segmentation. Certainly, Fully connected Convolutional Neural Networks (FCNNs)[4] were acquired for braincancer image segmentation in the Brain cancer Image Segmentation Challenge. More enhanced deep learning based brain cancer segmentation methods were introduced in the BRATS 2019 and different deep learning models were adopted, including FCNNs[6].

With the deep learning based brain cancer segmentation methods, the methods developed into CNN have produced more reliable execution. Most of the brain cancer segmentation methods train local regions in MR images[4]. This method classifies every image patch in various categories, like good tissue, disease, edema, non-enhancing core, and enhancing core[5]. These analysis effects of all image patches are used to label its center concerning finishing the brain cancer segmentation. Most of the above CNN brain cancer segmentation techniques concluded that every centroid's description is individualistic also that

People didn't take the attention and spatial coherence into an event[4].

Before Segmentation preprocessing, the dataset is required. The concentrations of several MRI scans are often normalized by decreasing their particular mean values and dividing by their specific variance values. We use slices collected in axial, coronal and sagittal appearances sequentially and join them to segment brain cancers engaging a deciding based merging approach. This proposed system can segment brain images slice-by-slice[4]. We assessed our method recommended imaging data afforded by the Multimodal brain cancer Image Segmentation Challenge (BRATS) 2013, the BRATS 2015, the BRATS 2016, BRATS 2017, BRATS 2018, BRATS 2019. The test outcomes have demonstrated that our method could produce encouraging brain cancer segmentation performance.

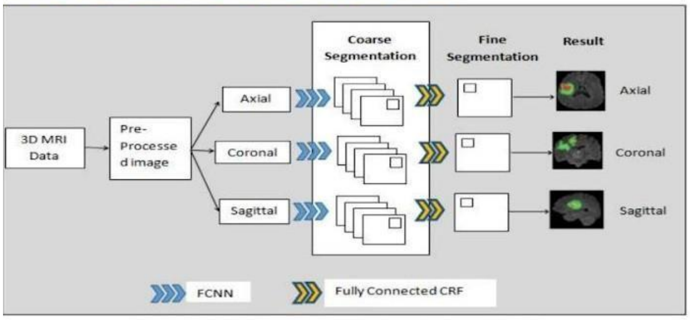

Figure 1: Architecture of our system

2.1 Imaging data

Every imaging data that we used were collected from the BRATS 2013, BRATS 2014, BRATS 2016, BRATS 2017, BRATS 2018, BRATS 2019[4]. The BRATS 2019 considered clinical imaging data about 335 glioma patients, including 76 patients with low-grade gliomas (LGG) and 259 patients with high-grade gliomas (HGG). Considering the four modalities of each patient's MRI they are, T2-weighted fluid-attenuated inversion recovery (Flair), T1-weighted (T1), T1-weighted contrast-enhanced (T1c), and T2-weighted (T2)[5]. We used skull stripped images. Manually generated ground truths are used. The cases were divided into training and testing sets. We used 52 HGG and 15 LGG cases for the training set[8].

Each imaging dataset considered by BRATS 2019 operates imaging data collected from the BRATS 2013, 2014, 2015, 2016, 2017, 2019 and also from TCIA. An individual case has Flair, T1, T1c, and T2 images arranged on a similar space of an anatomical template and inserted at 1 mm cube centroids resolution[4]. The testing dataset consists of 176 patients scans without knowing the type of glioma grades, and therefore the training dataset consists of 256 HGG and 76 LGG cases[8]. In the testing dataset, the ground truth of each patient was produced by manual segmentation.

2.2 Brain cancer segmentation methods based on FCNNs trained using image patches

We have used deep learning models, particularly the convolution neural network in image segmentation. CNN consists of more number of parameters. We can solve the problem considering it as an image classification problem by classifying the patches. While the training section, a large number of image patches are often extracted to coach the CNNs[4]. In the testing phase, image patches pulled out from a testing image are divided one by one by the trained CNNs. Then, the classification output of all image patches structures segmentation results of the testing image. The model is trained using a Fully connected convolution neural network and able to predict the classification of the image patches. The amount and site of training image patches for every class are often easily controlled by changing the image patch sampling scheme, image patch-based deep learning segmentation methods can avoid the training sample imbalance problem[4]. However, a restriction of image patch-based segmentation methods is that the relationship among image patches is usually lost.

2.3 Our Proposed Method for Brain Tumor Segmentation

The proposed brain cancer segmentation consists of pre-processing, segmenting image slices with deep learning models from different modalities of brain scan and using three slices of brain scan sagittal view, axial view, and axial views[4]. After segmenting, classifying the type of glioma and then predicting the survival of the patient.

2.3.1 Pre-processing of the imaging data

Considering MRI scan data typically have diverse strength scales and are suffering from leaning areas uniquely, we affirmed a strong normalization technique to make MRI image data of various cases equivalent, aside from improving the bias plot of MRI scan data utilizing N4ITK[4]. Our normalization approach is made upon the image pattern-based process, which normalizes image depth by deducting the image form (e.g. the gray-value of the most important histogram case) and normalizing the usual divergence to be one. As about division of the brain is the whiter matter, the gray-value of the most important histogram case typically compares to the gray-value of the white matter, and consequently rivaling depth rates of the white matter crossed MRI scanned image data and normalizing the depth sharing respectively would mostly execute various MRI scan image data equivalent.

Despite this, the feature aberration estimated sustained strength intimate doesn't significantly have a strong and quick tissue object. Accordingly, in our learning a strong emphasis divergence is chosen to reinstate the regular

Variation related to it. The strong divergence is figured based on the gray-value of the truly most helpful histogram case, describing the discreteness of strength to the gray-value of substantial[4]. Additionally, the intensity intend is extra delicate to noise than the grey value of the truly most helpful histogram case. Consequently the property variation estimated held intensity intend is extra delicate to noise than the strong divergence.

2.3.2 A deep learning Neural Network with FCNNs and Cascaded CRFs

The proposed deep learning model for brain cancer segmentation integrates Fully Convolutional Neural Networks (FCNNs) and cascaded Conditional Random Fields (Cascaded CRFs) [4]. We formulated Cascaded CRFs as Recurrent Neural Networks (RNNs), mentioned as Cascaded CRF-RNN[8]. The proposed method could segment brain images wedge by wedge.

(1) Fully Connected Convolution Neural Network

The edifice of our advanced FCNNs is represented, Related to the network structures suggested in the data to our network are also in two various sizes. Moving through a range of convolutional and pooling layers, the greater data becomes feature maps with a commensurate size of tinier input[4]. These feature maps and tinier inputs are carried into the following networks mutually. In this form, concern for organizing image views is taken by context information and local image data while a greater scale. Distinctive from the cascaded structure offered in the two sections in our FCNNs are instructed concurrently, rather than prepared in various tracks. Moreover, our form has more extra convolutional layers.

Our extracting from wedges of those views such as sagittal view, coronal view and axial views randomly, which is image patches are used to train the FCNNs model. Similar numbers of training units for various groups are excerpted to evade data imbalance problems [4]. There are five sections in total, including enhancing core, necrosis, non-enhancing core, healthy tissue and edema [5].

In our extensive FCNNs, the kernel area of each max-pooling layer is fixed to n x n, and the area of image pieces applied to instruct FCNNs is equivalent to the kernel area. Diverse contexts of the kernel area or proportionally the image bit area may harm the brain cancer segmentation completion [4]. The max-pooling layers of our FCNNs are wont to attract image erudition in massive measures with a comparatively less amount of network parameters. We began the pace of each layer to be unity. Therefore, in the trial stage, our design can segment brain images wedge by wedge.

(2) Cascaded CRF-RNN

Cascaded CRF-RNN formulates 2D fully connected cascaded Conditional Random Fields as Recurrent Neural Networks [4]. CRF is one of the most successful graphical models in computer vision. It is found that Fully Convolutional Network (FCN) outputs a very coarse segmentation results [8]. Thus, many approaches use CRF as post-processing steps to refine the output semantic segmentation map obtained from the network, such as DEEPLABV1 & DEEPLABV2, to have a more fine-grained segmentation results However, the parameters of CRF are not trained together with FCN. In other words, the FCN is unaware of CRF during training. This might limit the network CAPABILITY[11].

(3) The Fusion of FCNNs and Cascaded CRF-RNN

The prospective brain cancer segmentation network contains FCNNs and Cascaded CRF-RNN[4]. The FCNNs prophecy the possibility of choosing segmentation tags to every pixel, and the Cascaded CRF-RNN uses the prophecy results and image data as its data to globally optimize the surface and spatial density of the segmentation effects consistent with every pixel's strength and position erudition[8].

The intended deep learning interface of FCNNs and Cascaded CRF-RNN is qualified in 3 levels: 1) image patches are used to training FCNNs models; 2) practice Cascaded CRF-RNN utilizing image wedges with parameters of FCNNs set, and 3) fine-tuning the entire network relating image wedges.

The segmentation model is done while using the fine-tune of deep learning method, the model can be utilized to image wedges one by one for segmenting brain cancers. Read a w x t image wedge among three ways, i.e., pre-processed T1c, T2, and Flair scans image individually[5]. Taking these two more extended images as facts of the FCNNs, we receive five stamp predication images with the related area as the initial image wedges. Pi describes one pixel's anticipated prospect of brain membrane designs, like enhancing core, necrosis, healthy tissue and non-enhancing core[5]. Conclusively, the Cascaded CRF-FCNN concerns a globally utilized segmentation end of the initial image wedge[8].

In the instruction levels 2 and 3, we head estimate softmax damage consistent with the present segmentation effects and consequently the spot perfection, then the damage erudition is back-propagated to change material parameters of the amalgamated Cascaded CRF-RNN and FCNNs. In exercise level two, we set FCNNs and transform the parameters in Cascaded CRF-RNN[8]. In the exercise level three, we fix a little training speed and to tuning the parameters of the entire frameworks[6]. In our investigations, the primary training speed was fixed to 10^-5 and the training speed was distributed by 10 after every 20 periods in the exercise level

One, and the training speed was fixed to 10^-8 and 10^-10 sequentially.

2.3.3 Segmentation Results are integrated with all the Three Views

We instruct three segmentation patterns utilizing pieces and wedges of sagittal, coronal and axial scenes sequentially. While examining, we work these three patterns to segment brain images wedge by the wedge in three various scenes, allowing three segmentation outcomes. Each bulk polling tactic is obtained to combine the segmentation outcomes[4]. Make signify the segmentation outcomes of unit centroid obtained in sagittal, coronal and axial scenes sequentially, let r denote the segmentation result after fusion, let 0,1,2,3,4 denote a centroid labeled as healthy tissue, necrosis, edema, non-enhancing core, and enhancing core respectively.

2.3.4 Data Post-processing

To additional change the brain cancer segmentation execution, a post-processing classification is proposed. Hereinafter, V(T1c, Flair, T2), designate pre-processed T1c, Flair, T2 MR images sequentially, expresses the segmentation outcome achieved by our consolidated deep learning paradigm, and express the worth of centroid (x,y,z), Res(x,y,z)=0,1,2,3,4, symbolizes that the centroid (x,y,z) is marked as healthy tissue, edema, enhancing core, necrosis and non-enhancing core sequentially, Mean(Flair, T2) expresses the medium depth of the entire brain cancer field intimated by Res in V(Flair, T2) scans. For a segmentation outcome with 3D attached cancer fields, and Mean(T2(n)) express the normal strength of the nth 3D coupled brain cancer region in V(Flair, T2) sequentially[4].

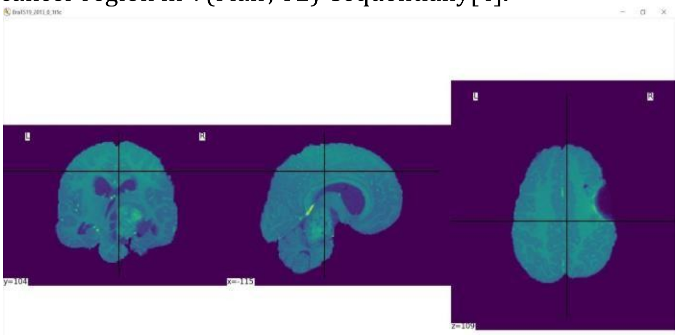

FIG 1: Image of T1c

3. Experiments

Our analyses were carried out based on imaging data provided by the BRATS 2013, 2015 and 2016, 2017, 2018, 2019 on a computing server with various Tesla K80 GPUs and Intel E5-2620 CPUs. However, only one GPU and one CPU were usable at the same time for our investigations. Based on the BRATS 2013 data, a range of investigations were carried out to evaluate how various implementation of the proposed program affects brain cancer segmentation results concerning Cascaded CRF, post-processing, image patch size, the number of coaching image patches, pre-processing, and imaging scans used. We also present brain cancer segmentation results obtained for the BRATS 2013. The brain cancer segmentation model was built upon the training data then evaluated and confirmed the testing data. Since no ground truth brain cancer segmentation result for the testing data was provided, all the segmentation results were evaluated by the BRATS evaluation website. The brain cancer segmentation performance was evaluated using the BRATS segmentation evaluation metrics for complete brain cancer, core region, and enhancing region, including Dice, Positive Predictive Value (PPV), and Sensitivity[4]. Particularly, the complete brain cancer involves necrosis, edema, non-enhancing core, and enhancing core; the core region includes corruption, non-enhancing core, and enhancing core; and the enhancing area only includes the enhancing core[5]. The brain cancer segmentation evaluation metrics are represented as follows:

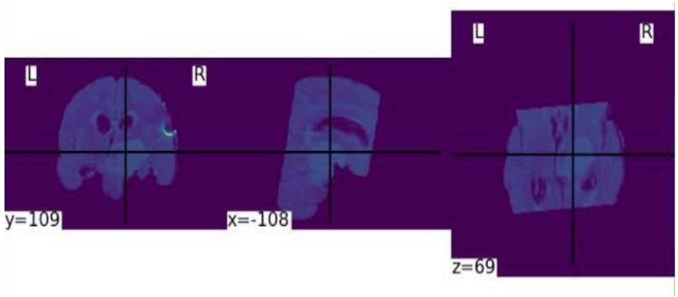

FIG 2: Flair scan of a patient

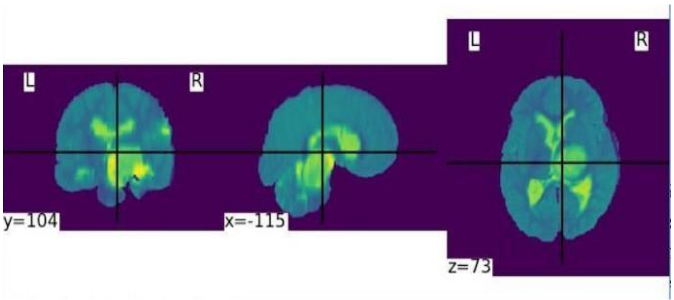

FIG 3: T2 scan of a patient

3.1. Working on BRaTs 2019 Dataset

The BRATS 2019 instructing dataset contains 76 LGG and 256 HGG. Several tests held conducted supported the BRATS 2013 dataset, including 1) analyzing the segmentation review of FCNNs with and externally post-processing, and

Consequently the design of the advanced deep learning network blending

Cascaded CRF-RNN[8] and FCNNs (hereinafter mentioned to as Cascaded CRF+FCNN) with and externally post-processing, to test the effectiveness of Cascaded CRFs and post-processing; 2) deciding the segmentation review of Cascaded CRF+FCNN with 5 post-processing steps (6 post-processing steps in total), to test the effectiveness of each post-processing step; 3) evaluating the brain cancer segmentation piece of FCNNs trained using diverse sizes of patches; 4) estimating the brain cancer segmentation performance of FCNNs trained using diverse quantities of patches; 5) examining the segmentation performance of segmentation bases constructed upon scans of 4 imaging chain (Flair, T1, T1c, and T2) and three imaging chain (Flair, T1c, and T2); and 6) Deciding how the image preprocessing level alter the segmentation representation. All the earlier experiments were performed in axial view. Apart from these tests described earlier, we attest the effectiveness of fusing segmentation outcomes of three views and decrease comparison returns with other classifications.

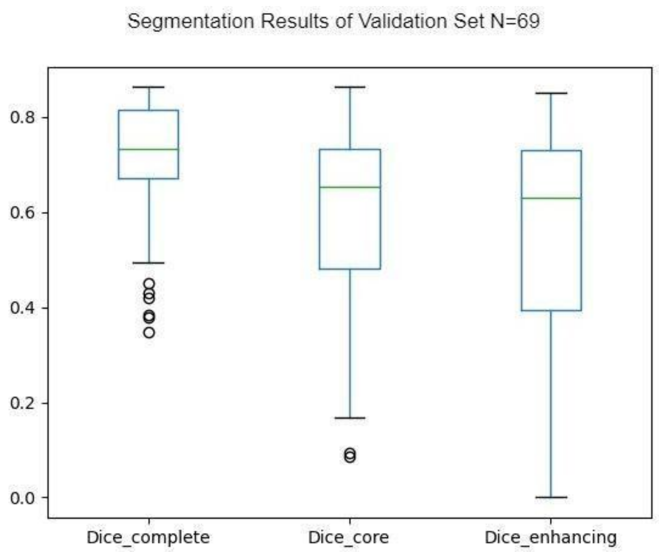

Fig 4: Result of validation Set of our Model

3.1.1. Evaluating of our Model

The evaluation outcomes of FCNNs with and without post-processing, and Cascaded CRF+FCNN (our integrated network of Cascaded CRF-RNN and FCNNs) with and without post-processing on the BRATS 2013 Difficulty dataset and Leaderboard dataset. These outcomes confirmed that Cascaded CRFs fixed the segmentation accuracy then did the post-processing. Concerning both Dice and PPV, FCNN process and FCNN+Cascaded CRF raised the segmentation performance in all complete brain cancer, core region, and enhancing region. However, Cascaded CRFs and post-process Decreased Consciousness. It is worth noting that Cascaded CRFs upgraded Consciousness of the enhancing area[5]. In summary, Cascaded CRFs improved both the Dice and PPV and reduced the Consciousness on the complete and core quarters, Cascaded CRF+FCNN process received the best performance concerning Dice and PPV, but demoted the performance concerning the Consciousness, especially on the whole brain cancer quarter. We also selected a 3D Cascaded CRF based post-processing step as did during a novel study. The parameters of the 3D Cascaded CRF were optimized by grid searching supporting the training dataset of BRATS 2013. Table 1 summarizes brain cancer segmentation counts gathered by our method with various environments. These results indicated that 3D Cascaded CRF as a post-processing step could upgrade the segmentation performance as 3D data was taken into evidence [8]. However, our proposed post-processing fashion could greatly promote the segmentation performance. We evaluate our prediction model with some indexes: average accuracy (ACC), sensitivity (SEN) and the average area under the receiver operating characteristic curve (AUC) values.

Comparison Table of Different Method

Method	Performance Score (dice Score)		
	Whole Tumor	Core Tumor	Active Tumor
Our Prediction	0.88	0.84	0.78
CNN with small 3 X 3 filter for deeper architecture	0.88	0.83	0.77
Generative model that performs joint segmentation	0.88	0.83	0.72
Cascaded two pathway model CNNs for simultaneous local and global processing	0.88	0.79	0.73

3.1.2. Evaluating the Results obtained in the three views produced by our Model

We practiced 3 segmentation figures utilizing pieces and wedges made in coronal, axial and sagittal views separately. While examining, we practiced these three figures to segregate the brain images from three aspects and obtained three segmentation outcomes. The outcomes of various aspects were combined and the evaluation outcomes.

Evaluation outcomes showed that, concerning both Hurdle and Leaderboard sets of data, blending the segmentation outcomes typically driven to more reliable segmentation representation externally the post-processing technique. Notwithstanding, the amendment enhanced unimportant behind the post-processing steps that were utilized for the segmentation outcomes.

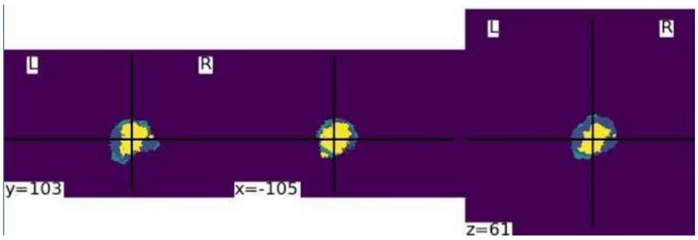

Fig 4: Ground truth scan of a patient

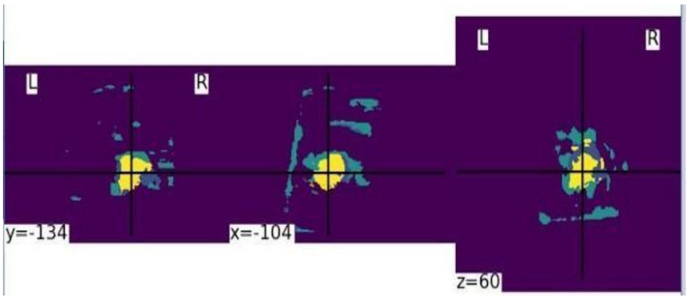

Fig 5: Segmented scan of a patient

4. Conclusions

In this learning, we intended a novel full learning-based brain cancer segmentation process by uniting cascaded Conditional Random Fields (Cascaded CRFs) and fully connected Convolutional Neural Networks (FCNNs) through a centralized structure. This combined standard was developed to concern brain cancer segmentation outcomes with spatial coherence and appearance. In our practice, we applied Cascaded CRFs to complete Cascaded CRF-RNN, expediting informal instruction of both

Cascaded CRFs and FCNNs as a whole deep network, preferably than utilizing after the post-processing step of FCNNs is Cascaded CRFs[4]. Our amalgamated deep learning pattern was qualified in three levels, utilizing image pieces and wedges independently. In the initiative, image pieces did n't instruct FCNNs. Certain image pieces did collectively inspected from the practice set of data and the related amount of image pieces for every position was applied as practice image pieces, to evade the results disproportion complexity. In the next move, image wedges were utilized to practice the subsequent Cascaded CRF-RNN, including parameters of FCNNs attached. In the next move, image wedges were appropriated to fine-tune the entire interface. Specifically, we instruct 3 segmentation paradigms utilizing 2D image pieces and wedges acquired in coronal, axial and sagittal views sequentially, and consolidate them to segregate brain cancers employing a polling-based coalition maneuvering. Our empirical outcomes also showed that some Alliance of Cascaded CRF-RNN[8] and FCNNs could enhance the segmentation clarity to parameters included in the design preparation, before-mentioned as image piece extent and the volume of practice image pieces. Our empirical outcomes also proved that a brain cancer segmentation standard established superimposed T1c, T2 and Flair scan accomplished competing achievement as these formulated upon T1, T2, T1c, and Flair scans[5].

We similarly intended a simple pre-processing approach and a simple post-processing approach. We pre-processed every MRI scan image utilizing magnitude normalization, which normalized every MRI scan image's strength chiefly by deducting the gray-value of the greatest balance and breaking the hale mutation[4]. The decisions that the intended consistency normalization technique could execute various MRI scan images identical, i.e., related strength grades portray alike brain networks across scan images. We post-processed some segmentation outcomes by eliminating pitiful 3D-connected areas and improving the wrong designs by an easy thresholding technique. Our preliminary outcomes have manifested that certain maneuverings could develop a brain cancer segmentation exhibition.

Our distribution has aimed at promoting execution on the BRATS 2014 and BRATS 2016 experiment dataset. Distinct from various top-ranked practices, our process could accomplish completion with hardly 3 imaging data modalities (Flair, T2 and T1c), fairly than 4 (Flair, T1c, T1, and T2) [5]. We also engaged inside the BRATS 2017 and our record placed the head on its multi-temporal evaluation.

Our approach is made by superimposed Cascaded CRF-RNN[8] and 2D FCNNs to realize computational representation. For practice fine-tuning and Cascaded CRF-RNN the amalgamated Cascaded CRF-RNN and FCNNs, we apply image wedges as a practice set of data. Despite image wedges, the estimates of pixels for various groups are distinctive, which worsens the segmentation execution of the practiced channels[5]. To partly overwhelm the imbalanced instruction dataset difficulty, we practiced the parameters of FCNNs with Cascaded CRF-RNN were set so that the Cascaded CRF-RNN is taught to optimize the facade and spatial coherence of segmentation outcomes. Such a plan in an organization among a fine-tuning of the entire interface with a tiny lore flow elaborated on the brain cancer segmentation execution. Yet, 2D CNNs are not decked to get the entire benefit of 3D erudition of the MRI image data. Our empirical outcomes have illustrated utilizing 3D Cascaded CRF[8] as a post-processing tread could develop the brain cancer segmentation representation[4]. Our continuing research is to constitute a thoroughly 3D interface to further grow brain cancer segmentation representation.

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