International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-9 Issue-3 September 2020

The Multi Stage U-net Design for Brain Tumor Segmentation using Deep Learning Architecture.

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***Abstract:** Now a day's diagnosis and accurate segmentation of brain tumors are critical conditions for successful treatment. The manual segmentation takes time consuming process, more cost and inaccurate. In this paper implementation of cascaded U-net segmentation Architecture are divided into substructures of brain tumor segmentation. The neural network is competent of end to end multi modal brain tumor segmentations.The Brain tumor segments are divided three categories. The tumor core (TC),the enhancing tumor(ET),the whole tumor (WT).The distinct data enhancement steps are better achievement. The proposed method can test result conclude average counter scores of 0.83268, 0.88797 and 0.83698, as well as Hausdorff distances 95%) of 2.65056, 4.61809 and 4.13071, for the enhancing tumor(ET), whole tumor (WT) and tumor core (TC) respectively. In this method validating with BraTS 2019 dataset and identify the test time enhancement improves the Brain tumor segmentation accurate images.*

***Keywords:** Deep learning · Brain tumor segmentation · U-Net*

I. INTRODUCTION

The Brain Tumor are unexpectedly rise of the cells inside of the brain and different types tumors .It consist of different level to low level grade gliomas(LGG) or high grade glimos(HGG). The Magnetic resonance imaging scan is most widely used scan. It can plays most important role in brain tumer segmentations. The Brain tumor segmentations of exact images to identify the disease of the tuomr growth and it helps to diagnosis treatment planning. The MRI images are generally using recovery methods such as fluid attenuated inversion recovery,T1 weighted (with and without contrast agent),and T2 weighted to analyse between different sub tissues[1].

Segmentation of brain tumor in medical images is a important and critical task that traditionally performed manually physicians. The Manual segmentation of the brain tumor takes more time and accuracy of the image less, So now a days we are using deep learning method using automatic Brain tumor segmentation to identify the tumor and deeply scan the tumor, increase the accuracy to detect the problem of the tumor stage condition[3].

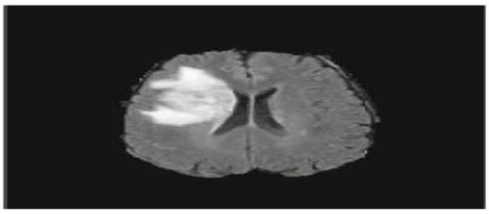
Image scanning currently using con deep learing based segmentation methods mainly consist of reconstruct placed and convolution based partion networks. The reconstruct the segmentation networks and small scale imagesalso a brain tumor segmentations.

The BraTS Challenges mainstream is image segmentation algorithm. The Convolutional neural network (CNN) is more effective and excellence over traditional methods. Different methods to identify the image scanning of the Brain tumor shapesmall patches are extracted

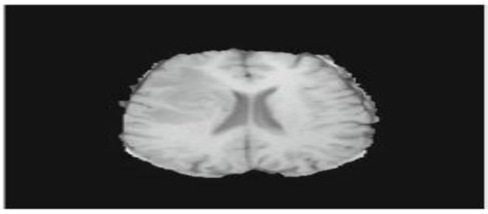
In Muti scale patches are different sizes of segmentations. U-Net is most of them used convolution network architecture. It is capture the background and symmetric expanding path locate the exact location of turmor in 3D extension[2].

The segmentation improve the model of images scan during the 3d U –net with different hyper parameters .tumor segmentation images are exact patches are clear to analyse the point of the circle to reduce the diseases.

In this paper proposed of multiple models and structure EMMA for secure segmentation.it achived by many network architecture including deep learning. The Network optimized in different process of loass functions such as dice loss and cross entropy loss.



T2 flair



T1 waighted

Revised Manuscript Received on September 15, 2020.

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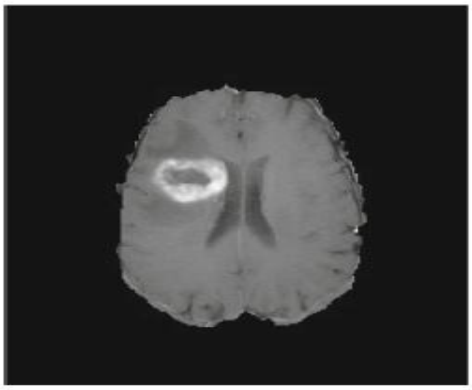

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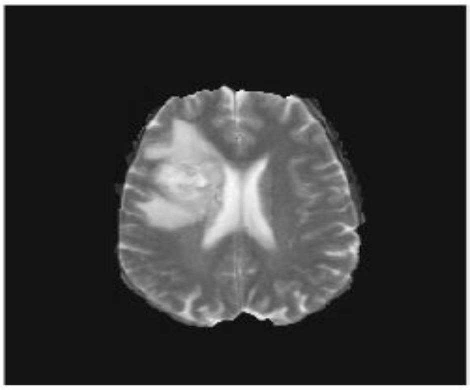

T2 wighted

Fig.1. Images of Brain tumor segmentation Methods.

II. LITERATURE SURVEY

TheBrain tumor segmentation previous years theoretical advances in the field and generation of low cost power consumption, in that added consumer-grade graphical processing units [17], there has been an outbreak of deep learning (DL) algorithms has been use more correlated techniques for solving major semantic segmentation problems in computer vision. In this model has a added advantage of being easy to implement by virtue of the multitude of mature tools available, most notable of these being TensorFlow [18] and PyTorch [1]. In this different methods and architectures that were specifically designed for segmenting 3- dimensional (3D) MRI images [2]. DL, specifically convolutional neural networks, segmentation problems in neuroimaging as including skull-stripping, obtaining good results [16]. most of these DL algorithms either require a long time to train or have unrealistic run-time inference requirements.

In the literature, convolution neural networks and its variants have manage the segmentation task. These structure use region-based segmentationapproach to achieve good results [10]. U-Nets have performed well in severalsegmentation challenges across the image processing domain [7–10,12,].The BraTS 2018 segmentation challenge. A large encoder has been used to extract deep learnig features. A decoder has been used to redesign the segmentation part. Variationalauto-encoders have been used to reduce the problem of over-proper [1].Kamnitsas et al., the winner of BraTS 2017, proposed an ensemble model calledEMMA (Ensembles of Multiple Models and Architectures) for robust segmentation.

III. PROPOSED METHOD

The Brain tumor segmentation is most use full to analze the diseases in now adays. In This paper proposed BraST 2019 Analyse the data sets using of network paths. The multi stages using improve the performance the data sets. Data sets are to analyse the data at a time 258 cases of high grade gliomas and low grade cases 77 manuallyby both clinicians and board-certified radiologists. In Every patient comparison with (T1), a post-contrast T1-weighted (T1Gd), a T2-weighted (T2) and a T2 Fluid Attenuated Inversion Recovery (T2-FLAIR) are provided. Generally fig 1 shows as a example of image set. Each tumor is segmented into enhancing tumor, the peritumoral edema, and the ecrotic and non-enhancing tumor core. The number of metrics (Dice score, Hausdorff distance (95%), sensitivity and specificity)

In this paper proposed of different models and structure EMMA for secure parts.it achived by multi network architecture including deep learning. The Network optimized in different process of loass functions such as dice loss and cross entropy loss. Proposed paper the network train of the architecture to reduce the entropy loss

In this proposed multi stage cascaded strategy, we propose a novel multi stage cascaded U-Net. In the first stage, we use a variant of U-Net.

1. First Stage of U-Net

The Model training method for small segmentation errors. that is pixel segmentation errors. The functional model dice loss for large images or large targets .in case of segmentation of Brain tumor images must be sharp functionala verify the point to point pixel rate. Previous method model training is a slightly error occurred analysis the vibrations of function loss. In this First stage of network train is most efficientsegmentation process[5]. In this stage increase widthof decode process.

2. U –Net using second stage

The moment of this stage is added advantage of forecasting map by prelimary indication of design of the pattern input to utilize the background. In this Stage not using any training data .Then only the test the result of the segmentation images.

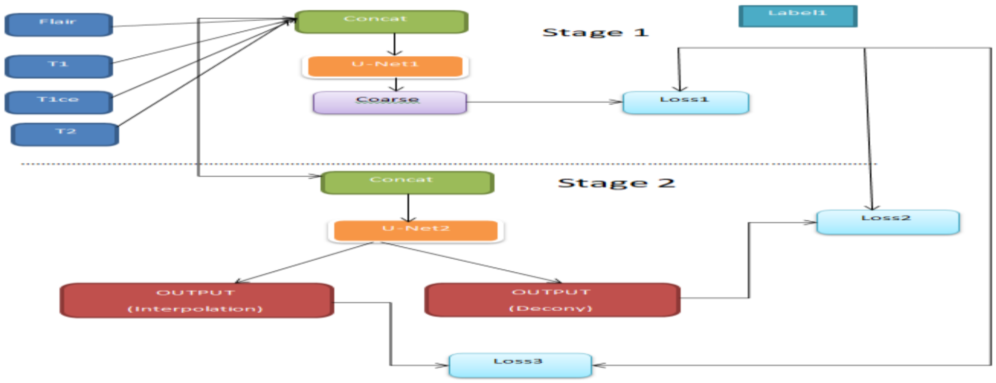

Fig .2. Multi stage or two stage Cascade network

IV. METHODS OF MULTI STAGE

Inthis Multi stage method first stage has a magnetic images (4 ẋ128 ẋ128ẋ128 voxels) are good stage and good efficiency of the segmentation of U-Net. The raw data design is deliver to the raw images in to U-Net of second part. Image segmentation accuracy must be little bit less .it over comes the multi moment of the U-net. The stage of second one must be good network Map with more parameters. The two stage or multistage data net as good accuracy of the segmentations. The two architectures are similar to contact but improve the good efficiency of network map.

A. Method of First Stage

The Network map design in different input patches of sizes 128ẋ128ẋ128 voxels and use size of the patch. The structure of the datapath high and complex sematic features. The segmentation maps has smaller decoding path and its recover same input sizes.network architectures, when overlook other parts of the system, that is processing of data. The larger networks are good generalise well by learning high-level absorption of the data, Then low intensity must be repeatedly input.The encoder and a decoder path interconnect block of lable, every level must be a 4 dimensions. Then first encoder block size 128×128×128 voxels with 4 channels are separate from the brain tumor images as input, an initial 3×3×3 3D convolution has 16 filters. The encoder part uses a pre-activated reusable part [5,6]. Then segment of patchs are consider in 2 3×3×3 convolutions established [8] with group size of 8 and Rectified Linear Unit (ReLU) activation, followed by additive identity skip connection.

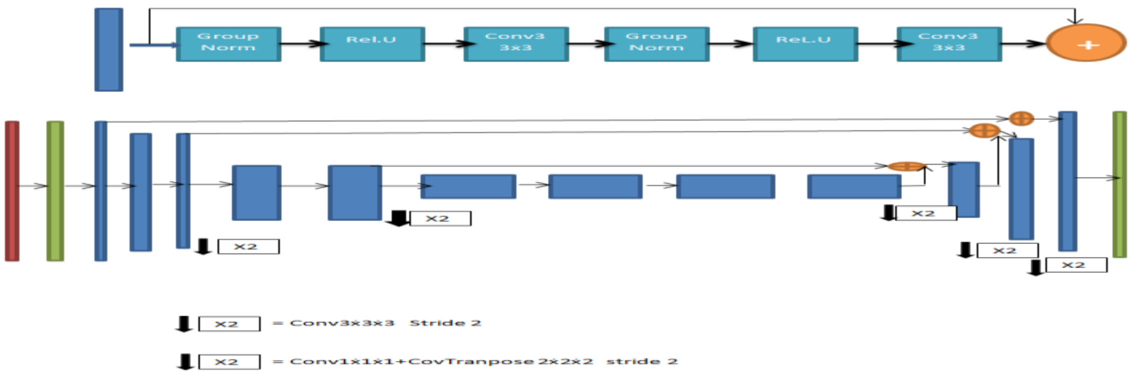

Fig 3. Network Architecture for stage 1

The number of reuse blocks is 1,2,2 and 4 with dimensional levels. Then convolution layers with 3ẋ3ẋ3 filters are a pieces of 2 used to reduce the resolution of the image. The exact path by 2. Continuously and increase the more channels. The encoder and decoder architecture reduce the number of factors of 2 compare witch deconvoulution with size of 2ẋ2ẋ2 and a piece of 2 .The interpolation order double size of the spatial domain. Design of decoder uses a single pre activated residual block. Before sampling convolution uses the 1ẋ1ẋ1ẋ1de- convolution. De-convolution canuses the sampling the structure of different segmentation blocks. The layer between connected with loss of the stage 1 to stage 2. Stage one module concat the different segmentation images and network map to analysis of the data path particular spatial domain.it has differ network layer interconnections.

Table 1.Convolutional neural network

Encoder	Name	Details	Repeat	Size
	Input			4x128x128x128
	InitConv	Conv3,Dropout	1	16x128x128x128
	EnBlock1	GN,ReLU,Conv3,GN,ReLU,Conv3,+	1	16x128x128x128
	Endownn1	Conv3 stride2	1	32x64x64x64
	Enblockn2	GN,ReLU,Conv3,GN,ReLU,Conv3,+	2	32x64x64x64
	Endownn2	Conv3 stride2	1	64x32x32x32
	Enblockn3	GN,ReLU,Conv3,GN,ReLU,Conv3,+	2	64x32x32x32
	Enbdown3	Conv3 stride2	1	128x16x16x16
	Enblockn4	GN,ReLU,Conv3,GN,ReLU,Conv3,+	4	128x16x16x16
Decoder	Deup3	Conv1,Conv transpose,+ EnBlock3	1	64x32x32x32
	DeBlock3	GN,ReLU,Conv3,GN,ReLU,Conv3,+		64x32x32x32
	Deup2	Conv1,Conv transpose,+ EnBlock2	1	32x64x64x64
	Deblock2	GN,ReLU,Conv3,GN,ReLU,Conv3,+	1	32x64x64x64
	Deup2	Conv1,Conv transpose,+ EnBlock1	1	16x128x128x128
	Deblock1	GN,ReLU,Conv3,GN,ReLU,Conv3,+	1	16x128x128x128
	EndConv	Conv1	1	3x128x128x128
	Sigmoid	sigmoid	1	3x128x128x128

B. Method of Second Stage

In this Second stage more number of stages used in 3D convolution. It must be increase the network width. This stage two decoders are used to implemented. The proposed method must be mose efficient for two stages U-net convolution methods increase the data path and in order to increase the point to point pixel rate. The Architecture of two decoder is same as deconvolution would beestabilishment. The decoder addition is gives the better performance. The decode uses the liner establishment method to repeatedlyand mutual encoder has better performance of the network data path.

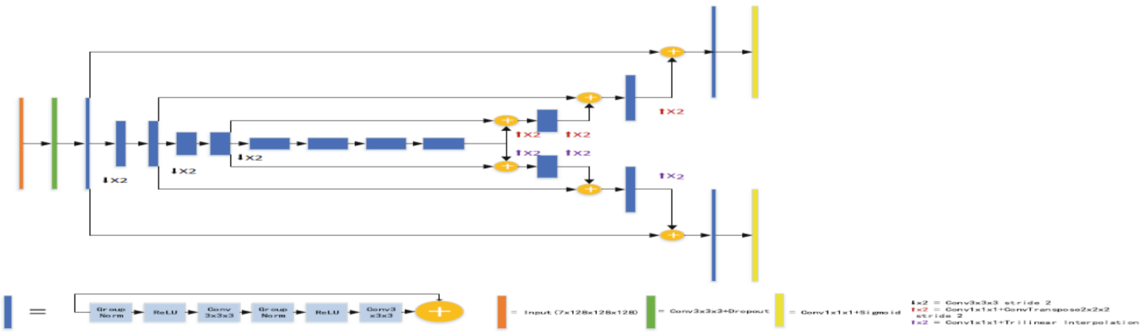

Fig 4Structure of Network second stage

1. Loss

The Loss generated on network overlap between the indicate the map and background of the truth table. The dice similarity coefficient (dsc) is finding using the expression,

$$DSC = \frac{2|A \cap B|}{|A| + |B|}$$

Where A is the network output.. B is the truth label background label and | is noted as the region.The Soft Dice Loss is expressed as

$$M = \frac{2 * \sum A * B}{\sum A^2 + \sum B^2 + \epsilon}$$

V. EXPERIMENTAL IMPLEMENTATION

A. Enhancement of Data Processing

The Data feed to deep learning network using a Pre-processing method of input data. Previous method using MRI intensity values nonstandardized.In this proposed method apply for Depth solution to each MRI scan modality from each patient freely. Brain region is a standard deviation to identify the part of the image. In this case overfitting problem generated. In that case apply for deploy data augmentation method .data augmentation deploy methods are three types[7]. The depth random scaling between the inputs [0.9-1.1].In that MRI data applied for network train it must randomly crop the images [240ẋ240ẋ155] voxels to 128ẋ128ẋ128 voxels due to memory limitations.

In this Proposed method implemented based on PyTorch 1.1.0 [14]. Its Depend on number of repetitions arefix to 405epochs with 5 band .More over better to restore the weight to implemented on dataset with size of the batch 1 and initial learning rate ἀ= le -4. It expressed as

$$\infty = \infty_0 \left(1 - \frac{e}{Ne}\right) 0.9$$

Where e is an epoch counter and Ne is a total number of epochs. Le-5 is decay weight.

B. Interference for Augmentation.

Brain tumor Segmentation whole brain region consist of different methods. The establishment of decoder is not useful for the interference phase .The input images are used different cast before deliver into network.

Table2. U-Net 2 second stage Network Architecture.

Table 2 shows the Structure of Second stage Network.

Encoder	Name	Deatails	Repeat	Size
	Input			7ẋ128ẋ128ẋ128
	InitConv	Conv3,Dropout	1	32ẋ128ẋ128ẋ128
	EnBlock1	GN,ReLU,Conv3,Gn,ReL,Conv3,+	1	32ẋ128ẋ128ẋ128
	EnBlockn1	Conv2 stride2	1	64ẋ64ẋ64ẋ64
	Enblockn2	GN,ReLU,Conv3,Gn,ReL,Conv3,+	2	64ẋ64ẋ64ẋ64
	Enblockn2	Conv2 stride2	1	128ẋ32ẋ32ẋ32
	Enblockn3	GN,ReLU,Conv3,Gn,ReL,Conv3,+	2	128ẋ32ẋ32ẋ32
	Enbdown3	Conv2 stride2	1	256ẋ16ẋ16ẋ16
	Enblockn4	GN,ReLU,Conv2,Gn,ReL,Conv3,+	4	256ẋ16ẋ16ẋ16
Decoder1	Deup3	Conv1,Con Transpose,+EnBlock3	1	64ẋ64ẋ64ẋ64
	DeBlock3	GN,ReLU,Conv2,Gn,ReL,Conv3,+		64ẋ64ẋ64ẋ64
	Deup2	Conv1,Con Transpose,+EnBlock3	1	32ẋ128ẋ128ẋ128
	Deblock2	GN,ReLU,Conv2,Gn,ReL,Conv3,+	1	32ẋ128ẋ128ẋ128
	Deup2	Conv1,Con Transpose,+EnBlock3	1	3ẋ128ẋ128ẋ128
	Deblock1	GN,ReLU,Conv3,Gn,ReL,Conv3,+	1	3ẋ128ẋ128ẋ128
	EndConv	Conv1	1	128ẋ32ẋ32ẋ32
	Sigmoid	sigmoid	1	128ẋ32ẋ32ẋ32
Decoder2(used only during training)	DeUp3-1	Conv1,Upsampling,+EnBlock1	1	64ẋ64ẋ64ẋ64
	DeBlock2-1	GN,ReLU,Conv2,Gn,ReL,Conv3,+	1	64ẋ64ẋ64ẋ64
	De Block2-1	Conv1,Upsampling,+EnBlock1	1	32ẋ128ẋ128ẋ128
	De Up2-1	GN,ReLU,Conv2,Gn,ReL,Conv3,+	1	32ẋ128ẋ128ẋ128
	DeBlock1-1	Conv1,Upsampling,+EnBlock1	1	3ẋ128ẋ128ẋ128
	EndConv-1	Conv1	1	3ẋ128ẋ128ẋ128
	Sigmoid-1	sigmoid	1	

Where + indicates The supplement identify leave the network,conv2 Transpose –deconvolution with the size 3×3×3, Upsampling –tracking additionally, Decoder 2can implemented on verifying the data

VI. RESULT

The variation of the Networks validation of the predict segmentation for BraTs2019 validate the dataset. In this paper proposed the 12 model sets for network train for data set validation.

The multi stage has most effective to analyse the network train to implement the Different cases. BrasTs 2019 approach validate the data in that consist of 126 cases with glioms grade and unknown segmentations. In This paper evaluate the Dice score ,senility specificity and Hausdoff distance (95%). Verification result can shown in table 3. Multi model or multi stage is verifying the dataset and validating result. Its good improvement for using multi stage minor comparisons for single stage.

Table 3

Method	Dsc			HD95		
Verification	WT	TC	ET	WT	TC	ET
Band of 5-fold	0.90796	0.85887	0.79666	4.35313	5.69196	3.12643
Best Single model	0.90818	0.86322	0.80198	4.44376	5.86202	3.20552
Band of 12 models	0.90941	0.86474	0.80212	4.26399	5.43932	3.14571

Table 3. Shown in Dice and Hausdoff measurements of the proposed segmentation method on BraTS 2019 validation data set .DSC is similar coefficient.HD95 Hausdoff. Distance (95%), WT –whole Tumor, TC –Tumor core, ET -Enhancing Tumor core

Table 4 shows The testing Method Results

Method	DSC			HD95		
Testing	WT	TC	ET	WT	TC	ET
Band of 12 models	0.88795	0.83698	0.831267	4.61819	4.13071	3..65057

VII. CONCLUSION

The proposedmethod a multi stage U-Net approach clarify the forecastover a good dynamic cascade network. Analysis on the BraTS 2019 acceptance set of implementations.In this paper proposed the 12 model sets for network train for data set validationin this mehod is very competing segmentation are implemented on single model. The testing results shows the proposed method to activeexcellent performance for network cascade stages. In this Multistage design implementation may increaser the perforce of network data validation in set of methods.

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