Brain Tumour Segmentation using Convolution Neural Network

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Abstract- Automatic brain tumor segmentation is an ill-posed problem. In this paper, we propose conditional generative adversarial networks (cGAN) based approach for brain tumor segmentation. cGAN comprises two networks namely generator to generate the brain tumor segmentation map and discriminator to validate the generator output. The proposed generator comprises encoder-decoder architecture. It encodes the input brain MRI slice into set of features using the encoder network followed by the generation of the brain tumor segmentation map from the encoded features using the decoder network. To maintain the structural consistency, feature maps obtained using a particular encoder are shared with the respective decoder using skip connections. Unlike existing encoder-decoder architectures, we processed the encoder feature maps through a convolution layer before sharing it to the respective decoder. It helps to refine the encoded features. We have used training set of the BraTS-15 dataset to train the proposed network for brain tumor segmentation. While, its testing set is used to validate the proposed network for brain tumor segmentation. The experimental analysis comprises the comparison of the proposed and existing methods for brain tumor segmentation with the help of Dice similarity coefficient and Jaccard index. Comparison with the existing methods show that the proposed method outperforms other existing methods for brain tumor segmentation.

***Keywords*—Tumour segmentation, CNN, cGAN**

1 INTRODUCTION

Gliomas, which originated from the glial cells and the surrounding infiltrative tissues, are the most malignant brain tumors in adults [1]. They are divided into low-grade gliomas (LGG) and high-grade gliomas (HGG), out of which HGG are the most aggressive one. At present, over 130 exclusive types of 'high-grade' and 'low-grade' brain tumors are regarded and the common survival is various between 12-15 months. Brain tumor segmentation is a hard venture due to their varied behavior each in terms of shape and feature [2]. Also, the tumor depth of 1 person differs drastically with others. Magnetic resonance imaging (MRI) is favored over different imaging modalities for analysis and remedy of brain tumors due to its non-invasive assets without the exposure to ionizing radiations and advanced image assessment in gentle tissues. Different sorts of tissue comparison images had been produced with the aid of MRI modalities, which permit extraction of treasured structural records consequently allowing diagnosis and remedy of tumors at the side of their sub-regions. MRI scans produced on applying exceptional pulse sequences are: 1) T1 weighted scans that distinguish normal tissues from tumorous ones. 2) T2 weighted scans to delineate the edema vicinity which produces bright photo vicinity. 3) T1-Gd scans use comparison agents that supply brilliant sign at tumor borders due to its accumulation. 4) FLAIR scans make use of signals of water molecule suppression which distinguishes Cerebrospinal fluid (CSF) from the edema region. For a Radiologist, these scans are useful to annotate specific regions of brain tumors. However, slice by slice annotation of brain tumors from MRI scans is an exhausting and time-consuming task. This burden can be replaced via automatic segmentation with the help of computer vision algorithms [3].

Computer vision techniques and computer- device development are emerging as research areas for the automated segmentation of brain tumors. Any of these methods have shown promising results but there is no winning strategy as these strategies have still not been used in hospitals literally. In recent times, convolution neural networks (CNNs) have become the technique of choice for state-of-the-art implementation of numerous image segmentation tasks [4]. BraTS [5] in tandem with MICCAI was the first one to apply CNN for brain tumor segmentation. Convolution layers use raw image intensities as inputs to measure the output image. It allows deep learning not to depend on handmade features of the brain MRI scan tumor segment. High levels of complexity in studying complex structures can be overcome by using non-linear algorithms and several qubits.

2 LITERATURE SURVEY

Through advances in machine learning techniques, support vector machine [6] and random forest [7] have been commonly used for automatic brain tumor segmentation. But such approaches allow hand-crafted features to be collected

for the learning of the corresponding machine learning model. Inspired by a deep learning methodology, Ronneberger *et al.* [8] first presented a totally convoluted U-Net framework in 2015. U-Net is built with a contractor path and a symmetrical expansion route with skip connections in between. Mirror methods have been used for boundary pixel prediction. Inspired by the U-Net model, Dong *et al.* [9] suggested a completely convoluted network for brain tumor identification and segmentation. The network was less effective in segmenting the enhancement area of the LGG cohort. In addition, the hybrid Pyramid U-Net brain tumor segmentation model is presented by Kong *et al.* [10]. They also expanded the U-Net model, which presents global context knowledge in a mix of specific regional contexts. Alex *et al.* [11] proposed clustering of brain tumors from multimodal MR images using a completely convoluted neural network (FCNN). They used a voxel-based classification of 23 layers and a single forward pass preceded by a false positive reduction using a linked component analysis. Havaei *et al.* [12] improved brain tumor segmentation output on the BraTS dataset. They used two-way and cascaded frameworks in their network. The two-way structure is used to identify two receptive fields for both local and global features. The pixel mark is determined on the basis of two factors, the visual characteristics of the marker and the location of the patch in the brain MRI scan. Wang *et al.* [13] generalized cascaded structure and used CNN for automated brain tumor segmentation. However, Hussain *et al.* [14] suggested a patch-based approach and used cascaded deep CNN for brain tumor segmentation.

In the field of semantic segmentation of natural scenes, the suggested encoder-decoder framework by Noh *et al.* [15] consists of specific convolution and pooling layers and shows high-resolution features in low-level conspicuous edges. Badrinarayanan *et al.* [16] suggested a revamped encoder-decoder architecture called SegNet, which overwhelms the drawbacks of [15]. The max-pooling indexes retain all information effectively without memorizing the float-precision feature maps, and the subsequent decoder shows the input feature map(s) using certain indices. Drozdzal *et al.* [17] expanded SegNet for the segmentation of brain tumors. In [8], authors used the benefits of identity mappings (*i.e. short skip connections*) rather than long skip links as used in U-Net. Such identity mappings support the creation of a deeper CNN without a gradient disappearing and allow rapid network learning with the proper recovery of the spatial information missed during down sampling. Researchers [18–20] have used small kernel sizes to build a deeper network architecture. Pereira *et al.* [20] added deep CNN 3×3 kernels. This model used less weights to obtain feature maps, thus reducing over-fitting. For both LGG and HGG, different architectures are used. The error caused by the incorrect classification of clusters was eliminated using a minimal volumetric restriction in the post-processing phase. Kamnitsas *et al.* [21] comes with a fully-connected, conditional random field (CRF) 3D CNN for precise brain lesion segmentation. The 3D CNN architecture is 11 layers deep and handles neighboring image patches in single pass with adequate tolerance to the inherent class disparity. They used dual route architecture for multi-scale feature extraction. Cui *et al.* [22] uses a tumor detection network and an intratumor classification network called a deep cascaded NN for brain tumor segmentation. Furthermore, Lin *et al.* [23] uses dense CRF-learning together with CNNs for segmentation refining. To boost tumor segmentation activity, Zhao *et al.* [24] used FCNN in combination with CRF. The above approaches were all focused on a patch-based approach in which medical scans were mostly separated into patches during training and testing. There is therefore a need for a model that takes whole medical scan as an input which can be used to address the data imbalance class by integrating both local and global features.

3 Related Work

Since last few years, adversarial training approach has been explored for most of the computer vision applications like image-to-image style transfer [25], image super-resolution [26], image depth-estimation [27], image de-hazing [28–31], moving object segmentation [32–37] (especially for image-to-image translation). Robustness of the adversarial training in image-to-image translation has been used in the medical image segmentation. Adversarial methods are commonly used in medical image processing with the potential to produce high quality results [38], [39]. Xue *et al.* [39] introduced an end-to-end adversarial network for brain tumor segmentation on MRI scan results. The classic generative adversarial network (GAN) architecture is the basic idea for this segmentor (*i.e. generator*) network as a FCNN for generating segmentation label maps and a critical network (*i.e. discriminator*) for multi-scale L1 failure. Two inputs were applied to the vital network: the actual brain MRI images are masked by ground truth label maps, and the actual brain MRI images masked by the predicted segmentor label maps. Segmentor and critical networks are alternatively trained in min-max manner: segmentor learning aims to reduce multi-scale loss of L1, while critical training aims to optimize the same loss function. In [40], author proposed an unpaired conditional adversarial training approach for brain tumour segmentation. Rezaei *et al.* [41] expanded conditional GAN [25] for brain tumor segmentation applications in MRI images. A semantic CNN and an adversarial network were proposed for BraTS 2017.

Inspired from the existing approaches, in this paper, we propose a conditional generative adversarial networks based approach for brain tumour segmentation. The highlights of the proposed work are listed below.

- Conditional generative adversarial network is proposed for brain tumour segmentation.
- A generator network is designed using residual learning and encoder-decoder architecture principles.
- Encoder feature refinement has been applied before sharing them to the respective decoder feature maps.

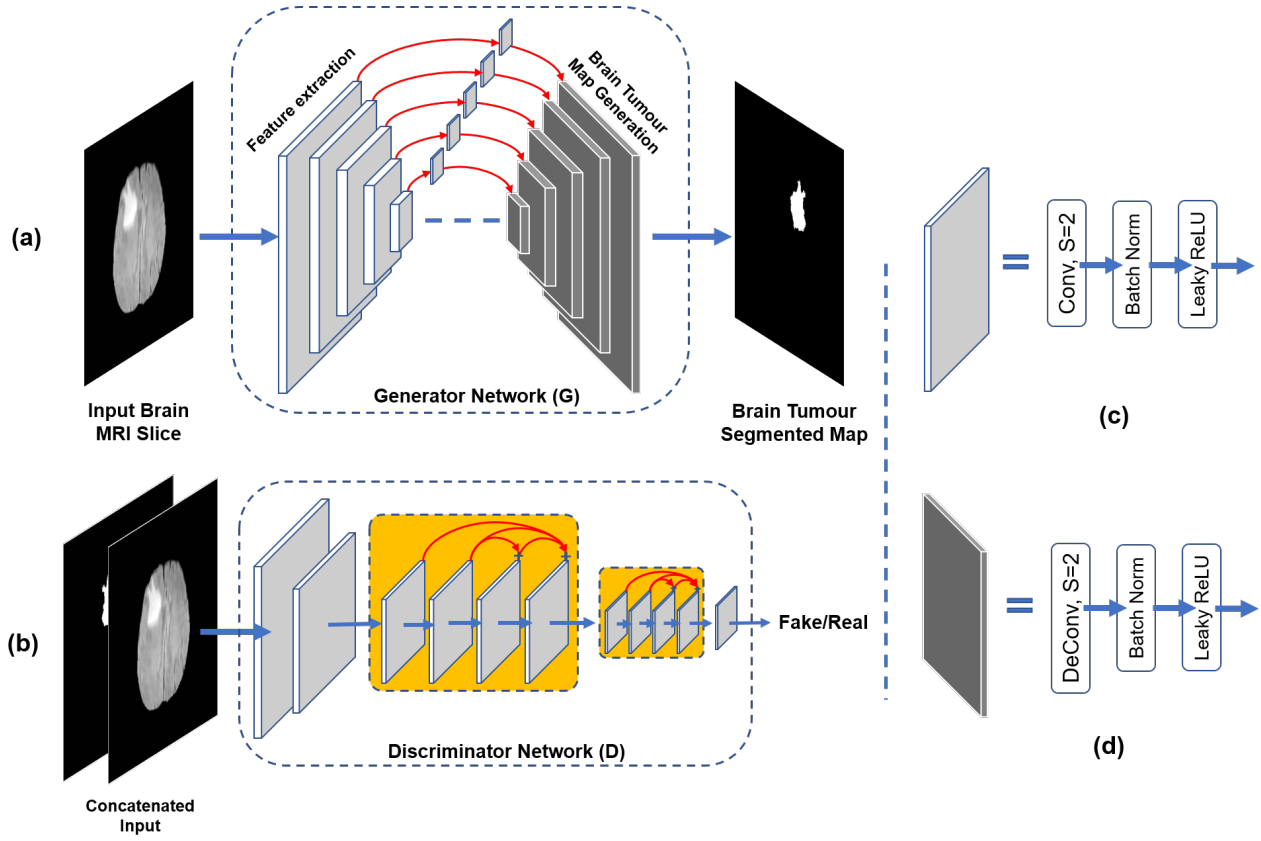

Figure 1: The proposed approach for brain tumor segmentation. (a) The proposed generator network (b) Discriminator network. Note: Red lines indicates the skip connections.

- The proposed network is validated on BraTS-2015.

Rest of the paper is organized as follows:
Section 1 and 2 illustrate the introduction and literature survey on brain tumor segmentation respectively. Section 3 discusses the related work to the proposed approach. Conditional generative adversarial network based approach for brain tumour segmentation is discussed in the Section 4. The proposed network training details are explored in Section 5. The experimental analysis has been carried out in Section 6. The conclusion about the proposed approach for brain tumour segmentation has been drawn in Section 7.

4 Conditional Generative Adversarial Network for Brain Tumor Segmentation

GANs are generative models that learn a mapping from random noise vector z to output image y, $G : z \rightarrow y$. In contrast, conditional GANs learn a mapping from observed image x and random noise vector z, to y, $G : \{x, z\} \rightarrow y$. In particular for the brain tumour segmentation, the generator G is trained to obtain the brain tumour segmentation map that cannot be distinguished from ground truth brain tumour map. Whereas, discriminator D is trained to differentiate between the generator output and the actual ground truth[1]. This training procedure is diagrammed in Fig. 1.

4.1 Objective

The objective of a conditional GAN can be expressed as,

$$\begin{aligned} \ell_{cGAN}(G, D) = \mathbb{E}_{\mathbf{x},\mathbf{y}}[logD(\mathbf{x},\mathbf{y})] \\ + \mathbb{E}_{\mathbf{x},z}[log(1 - D(\mathbf{x}, G(\mathbf{x}, z)))] \end{aligned} \tag{1}$$

G tries to minimize this loss function against D that tries to maximize it. Thus, $G^* = \arg \min_G \max_D l_{cGAN}(G, D)$.

[1]Details are given in [25]

4.2 The Proposed Generator Network Architecture

The proposed generator network comprises encoder-decoder architecture. It encodes the input brain MRI slice into set of features using the encoder network followed by the generation of the brain tumor segmentation map from the encoded features using the decoder network. The proposed generator network is divided into three parts *viz.* 1) Encoder 2) Decoder 3) Effective feature sharing approach as shown in the Fig. 1 (a).

4.2.1 Encoder:

The proposed generator network comprises eight encoder modules. Each encoder module consist of convolution layer followed by the batch normalization and leaky rectified linear unit (leaky ReLU). Here, convolution layer is designed for feature extraction. Whereas, the leaky ReLU is designed to generate the non-linearity in the network. Batch normalization is employed to normalize the learned feature maps. We keep Stride=2 in each convolution layer of the encoder module. Whereas, leaky factor=0.2 in each leaky ReLU layer.

The trail of the encoder modules follows a simple process *i.e.* feature extraction through convolution layer followed by the down-sampling operation. Thus, eight encoder modules process the input brain MRI slice of 256×256 size and finally reach a feature vector of size $1\times1\times512$. The proposed encoder module is shown in the Fig. 1 (c) and its use is shown in Fig. 1 (a) and (b).

4.2.2 Decoder:

Task of the decoder module is to decode the encoder feature maps and up-sample them to the next level. To maintain the network symmetry, we have designed eight decoder modules. Each decoder module comprises deconvolution layer with stride/up-sampling factor=2 followed by batch-normalization and leaky ReLU with leaky factor=0.2. Thus, with trail of the eight decoder modules, the proposed generator network finally generates the brain tumour segmentation map. The proposed decoder module is shown in the Fig. 1 (d) and its use is shown in Fig. 1 (a).

4.2.3 Modified feature sharing approach:

Together with the extraction of multi-scale features, there is a great importance of sharing features learned at initial layers across the network. For example, in [25] author shared the features learned at initial layers across the network for image-to-image translation task. Feature sharing approach turns to be effective in retaining the prominent edges in the desired output image map. Thus, to maintain the structural consistency, feature maps obtained using a particular encoder module are shared with the respective decoder module *via* skip connections. Unlike existing encoder-decoder architectures [8, 25, 42], we processed the encoder feature maps through a convolution layer before sharing it to the respective decoder. It helps to refine the encoded features and turned to be effective in retaining the prominent edge information relevant to the brain tumor segmentation. The modified feature sharing approach is shown by red arrows in the Fig. 1 (a).

4.3 Discriminator Network Architecture

We have used discriminator network proposed in [31] to discriminate the ground truth brain tumor segmentation map with one which is generated using the proposed generator network. It consists of the residual block with complex feature sharing for feature extraction. The discriminator network with the residual block is depicted in the Fig. 1 (b). Parameter details of the discriminator network can be found in [31]

4.3.1 Parameter details of the proposed generator network

Let a `3×3` Convolution-BatchNormalization-LeakyReLu layer (Encoder module) having `n` filters and stride '`2`' denoted as `cnv3sd2_LReLU-n`. Similarly, a `3×3` DeConvolution-BatchNormalization-LeakyReLu layer (Decoder module) with `n` filters and up-sampling factor '`2`' denoted as `deonv3up2_LReLU-n`. Skip connections between the encoder and respective decoder are as per shown in Fig. 1 (a). With this setting, proposed generator network is represented as, `cnv3sd2_LReLU-32` → `cnv3sd2_LReLU-64` → `(cnv3sd2_LReLU-128)×5` → `(decnv3up2_LReLU-128) ×4` → `decnv3up2_LReLU-64` → `decnv3up2_LReLU-32` → `decnv3up2 _LReLU-16` → `cnv3sd1_ Tanh-3`.

5 Network Training Details

In this Section, training details of the proposed network are discussed. The proposed network is trained for encoding input brain MRI image into set of features followed by generation of the brain tumor segmentation map from the encoded features. We make use of the BraTS-2015 database [5] to train the proposed network for brain tumor segmentation. It

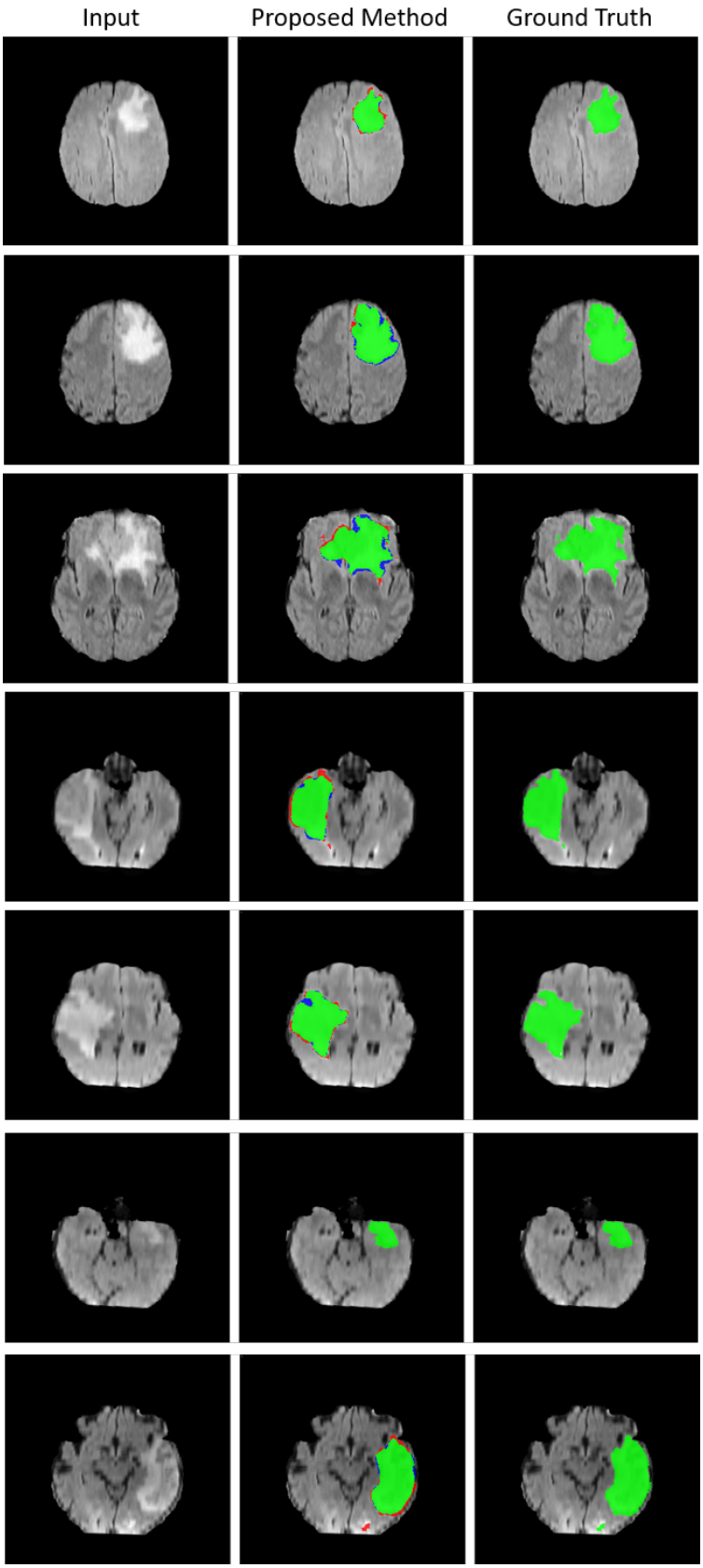

Figure 2: Visual results of the proposed approach for brain tumour segmentation. Brain tumour segmentation map obtained using proposed approach are mapped on the original brain MRI image. (a) Input brain MRI image (b) Proposed approach (c) Ground truth. *Green, red and blue color indicates the accurate segmentation, under-segmentation and over-segmentation respectively.*

Table 1: Performance comparison between the proposed method and existing state-of-the-art methods for the whole tumor segmentation on BraTS 2015 database. Note: DSC stands for Dice Similarity Coefficient

Method	**Publication year**	**Testing Data %**	DSC
Pereira *et al.* [20]	2016	15 %	0.78
Yi *et al.* [43]	2016	-	0.89
Dong *et al.* [9]	2017	-	0.86
Zhao *et al.* [24]	2018	18 %	0.8
Kamnitsas *et al.* [21]	2017	40 %	0.85
Cui *et al.* [22]	2018	10 %	0.89
Xue *et al.* [39]	2018	10 %	0.85
Kong *et al.* [10]	2018	30 %	0.8993
Proposed Method		**90 %**	0.9225

Table 2: Performance comparison between the proposed method and existing state-of-the-art methods for the whole tumor segmentation on BraTS 2015 database.

Method	**Publication year**	**Testing Data %**	Sensitivity
Pereira *et al.* [20]	2016	15 %	0.87
Zhao *et al.* [24]	2018	18 %	0.81
Kamnitsas *et al.* [21]	2017	40 %	0.88
Cui *et al.* [22]	2018	10 %	0.87
Xue *et al.* [39]	2018	10 %	0.8
Kong *et al.* [10]	2018	30 %	0.9581
Proposed Method		**90 %**	0.9553

consists of 220 HGG and 54 LGG patient scans. BraTS-2015 consists of FLAIR scans having resolution of $1\times1\times1$ mm^3 with an scan size of $240\times240\times155$. Each scan comprises of 155 brain MRI slices. We extracted 2D slices from each scan. In total, out of 14,415 MRI slices, we have considered only 10% slices to train the proposed network for brain tumour segmentation. The proposed network is trained on platform provided by GoogleColab.

6 Experimental Results

In this Section, we have analysed the performance of the proposed and existing methods for brain tumor segmentation. We have considered Dice similarity coefficient (DSC) and sensitivity to evaluate the performance of the proposed and existing methods for brain tumor segmentation. Mathematical formulation of the DSC and J is as follows:

$$DSC = \frac{2\,|A \cap B|}{|A| + |B|} \qquad J = \frac{DSC}{2 - DSC} \tag{2}$$

where, A and B are the brain tumor segmentation map generated by the proposed method and the ground truth brain tumor segmentation map respectively.
The experimental results are divided into quantitative and qualitative analysis discussed as follows.

6.1 Quantitative Evaluation

We have considered 90% brain MRI slices from BraTS-2015 dataset for quantitative analysis. There is no overlap of these 90% brain MRI slices with the training data. The quantitative evaluation of the proposed and existing methods is given in Table 1 and 2. Method [10] has the second best *i.e.* 0.8993 DICE similarity coefficient. Whereas the proposed method achieves highest *i.e.* 0.9225 DICE similarity coefficient. Interesting fact here is [10] validated their method on 30% brain MRI slices from BraTS dataset, on the other side, the proposed network is validated on 90%. Similar is the case with sensitivity. Method [10] achieves highest 0.9553 sensitivity value on 30% testing data. While, the proposed network achieves the 0.9553 sensitivity value with 90% testing data.

It is observed from the Table 1 and 2 that the proposed method outperforms the other existing methods for brain tumour segmentation in terms of the evaluation parameters.

6.2 Qualitative Analysis

Along with quantitative analysis, we have also carried out the qualitative/visual analysis. We have considered sample brain MRI images for the analysis. Figure 2 shows the brain tumor segmentation map generated using proposed approach. It is clearly observed from 2 that the brain tumor segmentation maps generated by the proposed method approaches towards the ground truth segmentation maps. We give this credit to the proposed generator network which is made up of encoder-decoder architecture with the proposed modified feature sharing approach. To show the effectiveness of the proposed modified feature sharing approach against the traditional feature sharing [8, 25], brain tumor segmentation maps generated using the proposed method (with modified feature sharing approach) and proposed method (with traditional feature sharing) are shown in the Figure 2. It is clearly observed that the proposed modified feature sharing approach based network outperforms the traditional feature sharing based network for accurate brain tumor segmentation task.

7 CONCLUSION

In this paper, we have proposed a brain tumor segmentation approach based on the conditional generative adversarial networks. It consists of two networks generator and discriminator. We have designed a encoder-decoder based generator network to generate the brain tumor segmentation map for given input brain MRI image. Unlike traditional approach, we propose a modified feature sharing approach to share the features learned at the encoder module across the network to the respective decoder module. We have utilized the 10% and 90% brain MRI slices of BraTS-2015 dataset to train and test the proposed network for brain tumor segmentation respectively. Both qualitative and quantitative analysis has been carried out to validate the proposed network for the brain tumor segmentation. The experimental analysis shows that the proposed method outperforms the other existing methods for brain tumor segmentation.

References

[1] N. R. Smoll, K. Schaller, and O. P. Gautschi, "Long-term survival of patients with glioblastoma multiforme (gbm)," *Journal of Clinical Neuroscience*, vol. 20, no. 5, pp. 670–675, 2013.

[2] Z. Li, Y. Wang, J. Yu, Y. Guo, and W. Cao, "Deep learning based radiomics (dlr) and its usage in noninvasive idh1 prediction for low grade glioma," *Scientific reports*, vol. 7, no. 1, p. 5467, 2017.

[3] Z. Wu, K. D. Paulsen, and J. M. Sullivan, "Adaptive model initialization and deformation for automatic segmentation of t1-weighted brain mri data," *IEEE transactions on biomedical engineering*, vol. 52, no. 6, pp. 1128–1131, 2005.

[4] J. Liu, F. Chen, C. Pan, M. Zhu, X. Zhang, L. Zhang, and H. Liao, "A cascaded deep convolutional neural network for joint segmentation and genotype prediction of brainstem gliomas," *IEEE Transactions on Biomedical Engineering*, 2018.

[5] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, Y. Burren, N. Porz, J. Slotboom, R. Wiest *et al.*, "The multimodal brain tumor image segmentation benchmark (brats)," *IEEE transactions on medical imaging*, vol. 34, no. 10, p. 1993, 2015.

[6] R. Ayachi and N. B. Amor, "Brain tumor segmentation using support vector machines," in *European Conference on Symbolic and Quantitative Approaches to Reasoning and Uncertainty*. Springer, 2009, pp. 736–747.

[7] A. Liaw, M. Wiener *et al.*, "Classification and regression by randomforest," *R news*, vol. 2, no. 3, pp. 18–22, 2002.

[8] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical image computing and computer-assisted intervention*. Springer, 2015, pp. 234–241.

[9] H. Dong, G. Yang, F. Liu, Y. Mo, and Y. Guo, "Automatic brain tumor detection and segmentation using u-net based fully convolutional networks," in *Annual Conference on Medical Image Understanding and Analysis*. Springer, 2017, pp. 506–517.

[10] X. Kong, G. Sun, Q. Wu, J. Liu, and F. Lin, "Hybrid pyramid u-net model for brain tumor segmentation," in *International Conference on Intelligent Information Processing*. Springer, 2018, pp. 346–355.

[11] V. Alex, M. Safwan, and G. Krishnamurthi, "Brain tumor segmentation from multi modal mr images using fully convolutional neural network," in *Medical Image Computing and Computer Assisted Intervention-MICCAI*, 2017, pp. 1–8.

[12] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P.-M. Jodoin, and H. Larochelle, "Brain tumor segmentation with deep neural networks," *Medical image analysis*, vol. 35, pp. 18–31, 2017.

[13] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks," in *International MICCAI Brainlesion Workshop*. Springer, 2017, pp. 178–190.

[14] S. Hussain, S. M. Anwar, and M. Majid, "Brain tumor segmentation using cascaded deep convolutional neural network," in *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*. IEEE, 2017, pp. 1998–2001.

[15] H. Noh, S. Hong, and B. Han, "Learning deconvolution network for semantic segmentation," in *Proceedings of the IEEE international conference on computer vision*, 2015, pp. 1520–1528.

[16] V. Badrinarayanan, A. Kendall, and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 12, pp. 2481–2495, 2017.

[17] M. Drozdzal, E. Vorontsov, G. Chartrand, S. Kadoury, and C. Pal, "The importance of skip connections in biomedical image segmentation," in *Deep Learning and Data Labeling for Medical Applications*. Springer, 2016, pp. 179–187.

[18] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[19] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[20] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in mri images," *IEEE transactions on medical imaging*, vol. 35, no. 5, pp. 1240–1251, 2016.

[21] K. Kamnitsas, C. Ledig, V. F. Newcombe, J. P. Simpson, A. D. Kane, D. K. Menon, D. Rueckert, and B. Glocker, "Efficient multi-scale 3d cnn with fully connected crf for accurate brain lesion segmentation," *Medical image analysis*, vol. 36, pp. 61–78, 2017.

[22] S. Cui, L. Mao, J. Jiang, C. Liu, and S. Xiong, "Automatic semantic segmentation of brain gliomas from mri images using a deep cascaded neural network," *Journal of healthcare engineering*, vol. 2018, 2018.

[23] G.-C. Lin, W.-J. Wang, C.-M. Wang, and S.-Y. Sun, "Automated classification of multi-spectral mr images using linear discriminant analysis," *Computerized Medical Imaging and Graphics*, vol. 34, no. 4, pp. 251–268, 2010.

[24] X. Zhao, Y. Wu, G. Song, Z. Li, Y. Zhang, and Y. Fan, "A deep learning model integrating fcnns and crfs for brain tumor segmentation," *Medical image analysis*, vol. 43, pp. 98–111, 2018.

[25] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2017, pp. 5967–5976.

[26] O. Thawakar, P. W. Patil, A. Dudhane, S. Murala, and U. Kulkarni, "Image and video super resolution using recurrent generative adversarial network," in *2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*. IEEE, 2019, pp. 1–8.

[27] P. Hambarde, A. Dudhane, and S. Murala, "Single image depth estimation using deep adversarial training," in *2019 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2019, pp. 989–993.

[28] A. Dudhane and S. Murala, "C2msnet: A novel approach for single image haze removal," in *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 2018.

[29] ——, "Ryf-net: Deep fusion network for single image haze removal," *IEEE Transactions on Image Processing*, vol. 29, pp. 628–640, 2019.

[30] ——, "Cdnet: Single image de-hazing using unpaired adversarial training," in *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 2019, pp. 1147–1155.

[31] A. Dudhane, H. Singh Aulakh, and S. Murala, "Ri-gan: An end-to-end network for single image haze removal," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2019, pp. 0–0.

[32] P. W. Patil and S. Murala, "Msfgnet: A novel compact end-to-end deep network for moving object detection," *IEEE Transactions on Intelligent Transportation Systems*, 2018.

[33] P. Patil, S. Murala, A. Dhall, and S. Chaudhary, "Msednet: multi-scale deep saliency learning for moving object detection," in *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2018, pp. 1670–1675.

[34] P. Patil and S. Murala, "Fggan: A cascaded unpaired learning for background estimation and foreground segmentation," in *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 2019, pp. 1770–1778.

[35] P. W. Patil, O. Thawakar, A. Dudhane, and S. Murala, "Motion saliency based generative adversarial network for underwater moving object segmentation," in *2019 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2019, pp. 1565–1569.

[36] P. W. Patil, A. Dudhane, S. Murala, and A. B. Gonde, "A novel saliency-based cascaded approach for moving object segmentation," in *International Conference on Computer Vision and Image Processing*. Springer, 2019, pp. 311–322.

[37] P. W. Patil, K. M. Biradar, A. Dudhane, and S. Murala, "An end-to-end edge aggregation network for moving object segmentation," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 8149–8158.

[38] D. Nie, R. Trullo, J. Lian, L. Wang, C. Petitjean, S. Ruan, Q. Wang, and D. Shen, "Medical image synthesis with deep convolutional adversarial networks," *IEEE Transactions on Biomedical Engineering*, 2018.

[39] Y. Xue, T. Xu, H. Zhang, L. R. Long, and X. Huang, "Segan: Adversarial network with multi-scale l 1 loss for medical image segmentation," *Neuroinformatics*, pp. 1–10, 2018.

[40] S. Nema, A. Dudhane, S. Murala, and S. Naidu, "Rescuenet: An unpaired gan for brain tumor segmentation," *Biomedical Signal Processing and Control*, vol. 55, p. 101641, 2020.

[41] M. Rezaei, K. Harmuth, W. Gierke, T. Kellermeier, M. Fischer, H. Yang, and C. Meinel, "A conditional adversarial network for semantic segmentation of brain tumor," in *International MICCAI Brainlesion Workshop*. Springer, 2017, pp. 241–252.

[42] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *IEEE International Conference on Computer Vision*, 2017.

[43] D. Yi, M. Zhou, Z. Chen, and O. Gevaert, "3-d convolutional neural networks for glioblastoma segmentation," *arXiv preprint arXiv:1611.04534*, 2016.