Journal of Autonomous Intelligence (2024) Volume 7 Issue 5
doi: 10.32629/jai.v7i5.1058

ORIGINAL RESEARCH ARTICLE

Segmentation of tumor regions using 3D-UNet in magnetic resonance imaging

Divya Mohan[1,*], Ulagamuthalvi Venugopal[2], Nisha Joseph[3], Kulanthaivel Govindarajan[4]

[1] *Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai 600119, India*

[2] *Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai 600119, India*

[3] *Computer Science and Engineering, SAINTGITS College of Engineering Autonomous, Kerala 686532, India*

[4] *Department of Electrical Electronics and Communication Engineering, National Institute of Technical Teachers Training and Research (NITTTR), Chennai 600113, India*

*** Corresponding author:** Divya Mohan, divyamohanresearch@gmail.com

ABSTRACT

Brain tumor has been a severe problem for a few decades ago. With the advancement in medical technologies, a brain tumor can be treated if observed earlier. This paper aims to segment and classify the tumor regions from Magnetic Resonance Imaging (MRI). The work consists of two steps. In step1, the 3D MRI images are pre-processed by the Salient Object Detection method to improve efficiency. In step2, the improved 3D-Res2UNet segments the tumor regions. The segmented tumors are partitioned into two classes using a Support Vector Machine (SVM) classifier. The method is tested using BRATS 2017 and 2018 datasets and obtained 87.1% and 99.2% dice score for BRATS 2017 and 2018, respectively. The performance of the proposed method is better compared to most recent methods.

Keywords: tumor; residual network; UNet; classifier

ARTICLE INFO

Received: 27 July 2023
Accepted: 1 December 2023
Available online: 8 March 2024

1. Introduction

Brain tumor is one of the severe diseases from several years ago. It can be cured when it is detected early. Some factors also measure the severity and the volume of the disease. The severity of the disease is categorized into LowGradeGlioma (LGG) and HighGradeGlioma (HGG). The volume of the tumor is measured in cubic centimeters. Medical technology prevents ill-human from the possibility of death. The medical experts use segmentation models to segment tumor portions in the brain quickly. There are several automatic brain tumor detection methods that detect and classify the type of tumor.

The brain tumor diagnosis is quickly made in MRI. In the paper of Wang et al.[1], a cascade of Convolutional Neural Networks (CNN) for the separation of brain tumors from MRI was introduced. The Anisotropic-RegCascade uses a hierarchical cascade of three networks, one for each of the three tumor regions, and ensembles three different cascades, one trained for each 3D view. This method is a trade-off between computational cost and model complexity. Xu et al. used an architecture composed of a regular feature extractor that branches out to an attention-guided cascade of three relatively more minor 3D U-

Nets to segment each hierarchical tumor sub-region[2]. Each U-Net contains feature bridge modules and attention blocks coupled with the cascade to achieve a competitive segmentation performance.

An Enhanced Convolutional Neural Network using updated loss function with BAT algorithm was introduced in the work of Thaha et al.[3]. Hu et al. segmented brain tumors using a MultilevelUpsampling Network (MU-Net)[4]. They employed the global attention block to integrate the encoder's low-level feature outputs of encoder section with the stand-high-level feature outputs of decoder.

Tuan T. et al. used a UNet model with several kernels to segment all glioma areas[5]. Weninger L. et al. employed 3DUNet to segment the tumor after determining its location[6]. A 3D-Usid-Unet architecture[7] was designed by Hu X et al., which featured a semantic collection path and a localization path. To diagnose aberrant tissues with various labels, a robust random tree algorithm was trained by Serrano-Rubio et al.[8].

The severity and importance of brain tumour detection is mentioned in the research of Miller et al. [9]. Based on this study malignant tumor is increasing every year in children, adolescents and male compared to females. Whereas non-malignant tumour rate is high among females. Prevention, early detection and treatment are the normal procedures to be followed for survival from tumors and the early detection is very much crucial for saving patients from death.

The main contributions of this paper include the following:

- SOD—Only brain portions are segmented from each 3D slice. This method reduces the computational burden caused by the size of the dataset.
- 3D Res2UNet—Improved ResNet is used to segment the tumor. It yields segmentation with better accuracy.
- SVM Classifier—After segmenting the tumor, the type of tumor is classified using the SVM classifier.

Nowadays deep learning techniques are used in medical image processing which increases the accuracy, reduces the computation time and automate the detection and classification process. Since the MRI image is 3D containing sequence of 2D images, the computation overhead is high if the input 3D image is directly given to the system. So to reduce the first 2 dimensions in all the slices the SOD algorithm is very much helpful. The Res2Net represents multi-scale features at a granular level and increases the range of receptive fields for each network layer. 3D Unet captures features in adjacent slices in the input MRI image. Hence combination of Unet with Res2Net improves the performance significantly by reducing the computation overhead.

The paper is organized as follows: Part 2 explain the existing literature in brain tumor segmentation field. Part 3 explains the functional architecture of the method proposed. Part 4 deals with presentation and analysis of experimental results. Part 5 concludes the work providing future enhancements.

2. Related works

The brain tumor methodologies that use deep learning network models are discussed briefly in this part. With lacking modalities, a new brain tumor segmentation method[10] was described. A correlation model was built to capture the latent multiple source correlation.

A cross-modality deep feature learning system[11] was built to separate brain cancers from MRI images. The goal was to find rich patterns present all over the multiple modality data, to compensate for the lack of data size. The transition of cross modality feature and fusion of features were two learning processes in this technique. It learned additional feature representations by transiting information over multiple modality data and integrating extracted inference from them.

The SegSE block[12] combined the features with a spatially adaptive recalibration block for semantic segmentation with fully convolutional networks. Cross-channel information and geographical relevance were used to adjust feature maps. In the work of Rehman et al.[13], a BrainSeg-Net model had been developed based on encoder-decoder technology. The feature enhancer block had been introduced to the BrainSeg-Net design, which took the middle-level features extracted from the low level feature map input of shallow layers and shares them with the dense layers. This feature aggregation aided in improving tumor detection performance. A loss function was designed and applied to solve the class imbalance issue.

To improve the performance of the model techniques like—dilated convolution, adding skip connection, using dense units, and incorporating MultiRes block—were used in the fundamental U-Net to do image segmentation[14]. Multi-modalities fusion, tumor extractor, and tumor segmenter were 3D deep neural network components that conduct tumor segmentation on pre-processed multi-modalities[15]. The weighted segmentation loss function based on the Jaccard index and the dice coefficient addressed the problem of class imbalance.

To enable real-time dense volumetric segmentation, a highly efficient 3D CNN was introduced[16]. The network used a 3D multiple fiber unit comprising a group of lightweight 3D CNN to reduce runtime costs drastically. Furthermore, multi-scale feature representation was built using 3D dilated convolutions.

A pre-processing strategy had been employed solely on a small picture area rather than the entire image to generate an effective and flexible model separating brain tumor[17]. This strategy reduced runtime overhead and solved overfitting in a CascadeDeepLearning model (C-CNN) which had a fundamental and efficient neural network works with smaller brain regions present in each slice. The C-CNN model extracted global and local characteristics in two independent ways. A DistanceWiseAttention (DWA) method was also used to increase accuracy. The DWA process influenced the tumor's central position and the brain inside the model.

For automated brain lesion segmentation, a two-stage supervised learning system had been used[18]. The first random forest classifier was trained using intensity oriented statistical features, template oriented asymmetric features, and Gaussian Mixture Model (GMM) associated probability maps of tissues. The dense Conditional Random Field (CRF) was then utilized to refine the RF classifier's probability maps and derive the whole tumor area. Following that, the optimal probability maps were intergraded with template oriented asymmetric and intensity oriented statistical features to learn the following RF, focusing on identifying voxels inside the tumor area.

Zhang et al.[19] had created a TaskStructuredBrainTumor Segmentation (TSBTS) network to replicate radiologyst's competence by looking at both the task-task structure and task modality. The task modality structure found distinct tumors by considering dissimilar volume data in various modalities, which exhibits different clinical traits. In contrast, the task structure found the most distinct area with one portion of the tumor utilizing which another similar component was located nearby.

A genetic approach generated automatic brain tumour segmentation[20]. For noise reduction, a homomorphic wavelet filter was utilized. After that, a Non-dominated Sorted Genetic Algorithm (NSGA) was used to pick the extracted features from the inceptionv3 pre-trained model. Tumor slices were submitted to the YOLOv2-inceptionv3 model after the optimized features were forwarded for classification. The localized pictures were submitted to McCulloch's Kapur entropy algorithm.

Another technique [21] used deep CNNs to identify LGG from HGG on conventional MRI images in an automated, non-invasive manner. In the research of Narmatha et al. [22], a fuzzy brain-storm optimization technique had been developed for medical picture segmentation and classification. The cluster centers were given the greatest priority in the brain-storm optimization process. To propose an optimum network structure, the fuzzy did numerous rounds. **Table 1** describes summary of a few related works.

Table 1. Summary of related works.

Model	Advantage	Disadvantage
Multi source correlation model[10]	Best suited if one of the four modalities is missing	Computation overhead
Task-structured brain tumor segmentation network (TSBTS net)[11]	Better performance, Lower computational cost	Complex model
Semantic segmentation with Fully Convolutional Networks—the SegSE block[12]	Adaptive recalibration block to suppress less relevant features	Processing overhead
BrainSeg-Net[13]	Shares extracted middle level features from shallow layers to dense layers	Connection overhead
End to end brain tumor segmentation with Fully Convolutional Neural Network[14]	Improves information flow, learns richer representations, Segment brain tumour sub regions	Can test with BRATS 2018 and higher
Multi-modality encoded fusion with 3D inception U-net and decoder model[15]	Solves class imbalance problem, segments 3 regions into five classes.	Can test with BRATS higher
3D Dilated Multi-Fiber Network[16]	Reduces computation cost, Improves accuracy	Can test with BRATS higher

3. Proposed methodology

UNet[23] is a semantic segmentation model developed based on a fully convolutional neural network. Recent literature reveals that the three-dimensional variation of UNet accurately segments medical images. The UNet can be further improved by adding residual layers to solve the multiple layers learning problems. The residual layers protect the data integrity and increase the network training speed. This paper proposed to use an improved version of UNet by integrating 3D UNet and residual network, i.e., Res2UNet.

The computation burden of using a 3D dataset is reduced by including the SOD method. The SOD method segments only the brain regions in the 3D MRI images. Then the 3DRes2UNet is employed for segmentation and feature extraction. Finally, the segmented tumors are classified using a multiclass SVM classifier. The process flow is depicted pictorially in **Figure 1**.

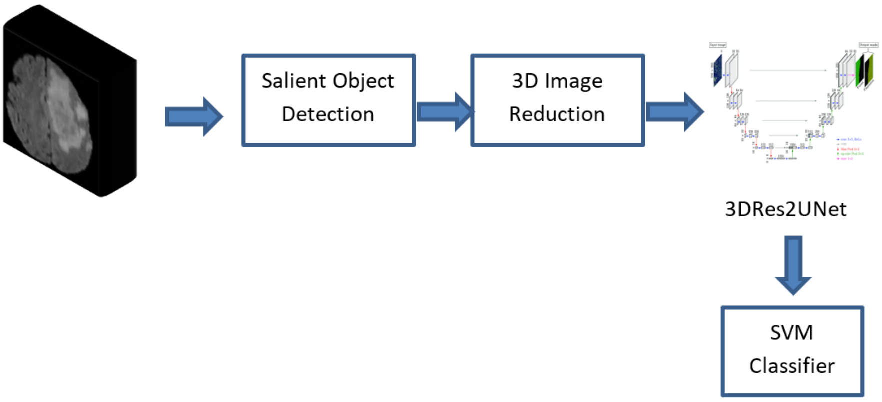

Figure 1. Proposed system architecture.

3.1. Salient object detection

Salient objects are the most relevant object in an image. Gupta et al.[24] mentioned different types of salient object detection methods. In this work, the brain area in the MRI is considered as the salient object. In an MRI image slice, the brain occupies significantly small portions. So the separation of brain region is performed using the algorithm SOD[25]. This algorithm generates a saliency map from which salient objects (i.e., brain) are segmented. To create saliency map, detection windows are created using maximum proximity principle and subset optimization optimal detection windows are selected as saliency map. Using the saliency map the region of interest is cropped from all slices of MRI input image having multiple modalities.

The Dataset BRATS contains multi-plane data. It was found that some planes did not contain a salient object. It is essential to identify whether a slice contains a salient object or not, the regions of the corresponding portions are segmented if there is an object. Otherwise, the plane is skipped.

3.2. 3D image reduction

The size of each 3D MRI in the BRATS dataset is 240 × 240 × 155. As the planes that do not contain salient objects are skipped, the size of the 3D MRI is reduced. Similarly, only the brain portions are used for the plane with a salient object. Thus, the first two dimensions are also reduced to the detection window size. The detection window size is fixed in the SOD algorithm. It is calculated based on the size of the brain regions in the MRI image. The first two dimensions are expected for an entire input image. Nevertheless, the third dimension depends on the salient object presence in each plane.

Since the reduced 3D MRI input images are given to the deep network model, the size of all the images should be the same by including a few slices. It has been studied that this inclusion does not affect the accuracy of tumor segmentation based on some experiments.

3.3. 3D Res2UNet feature extraction

This work includes the 3D-Res2Net as part of 3D-UNet to create an architecture, namely 3DRes2UNet. The architecture of the 3D-Res2UNet is presented in **Figure 2**.

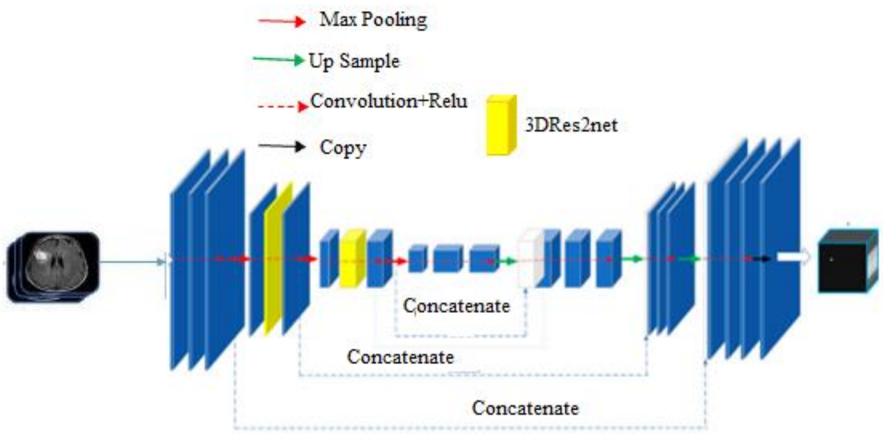

Figure 2. 3DRes2Unet architecture.

The 3D-Res2UNet CNN uses 3D-Res2Net unit instead of the 3D basic convolution unit by changing the original CBR unit (Conv + BN + ReLU). The 3D-Res2Net unit included in 3DRes2Unet is presented in **Figure 3**[26]. It has two main stages: - down sampling and up sampling. It uses convolution, Relu and max pooling operations using group filters mainly. The architecture of the basic residual unit is changed by 3D-Res2Net. This unit alters the original filter with numerous 3 × 3 × 3 filter sets and mixes distinct filter groups instead of the basic residual unit. It means each filter in the block comprises of a number of group (cardinality)of small 3 × 3 × 3 filters which in turn extracts granular features from corresponding division of input feature. A new residual layer connection is created by joining the residual cascade. After the last 1 × 1 convolution, a 3D Squeeze and Excitation block (SE block) is added to recalibrate feature output from each channel by taking into consideration of inter channel feature dependencies to reallocate weight.

After the 1 × 1 × 1 convolution, the four feature groups of the 3D-Res2Net module are transformed into eight channels[27]. The first feature map x1 is mapped to y1 using identity function which reduces the number of parameters to be maintained over the network during training hence reduces computational overhead associated with parameter updates. The Res2Net part extract minute features helping the separation process positively which enhances the accuracy. The UNet part extracts inter slice feature associations. Furthermore, x1 corresponds to the output feature from channels 1 and 2, whereas x2 denotes the output feature from channels 3 and 4. The weight associated with the convolution filter adjusted by each grouped channel differs during training and grouping time of corresponding channels. The concatenation operation is done on y1, y2, y3, and y4 to keep the channel intact. Two factors support the straightforward mapping of the initial x1 to y1. The first is to decrease the number of parameters associated with the network and corresponding computation overhead, and the second reason is that it permits the reusing of features obtained in various stages which increases the accuracy.

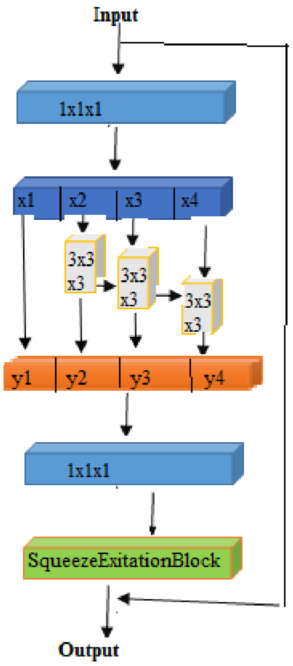

Figure 3. The 3D-Res2Net unit structure.

4. Experimental results

It provides an analysis of suggested method with some experiments. Initially, it presents details regarding the datasets used to evaluate the method, followed by performance measures and the obtained results. Finally, the performance of suggested method is compared with that of current methods, and detailed discussion is done.

4.1. Dataset used

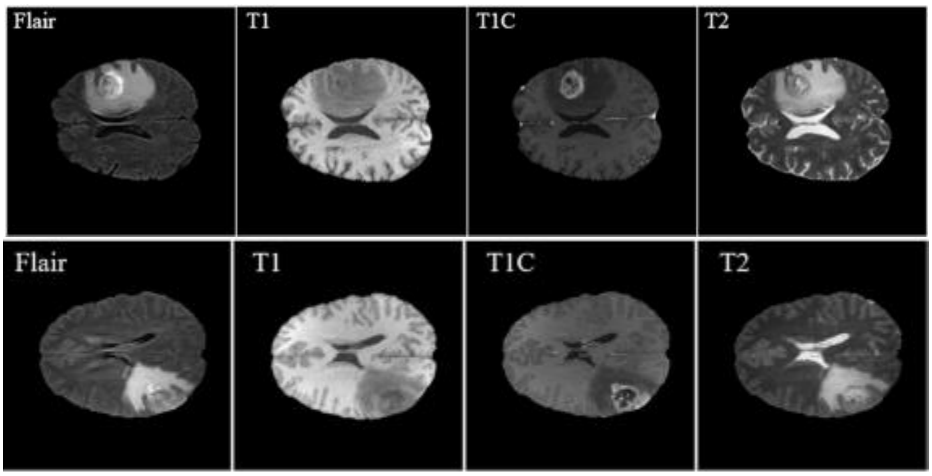

Figure 4. Examples of BRATS Dataset.

The suggested method is tested using two publicly available Datasets-BRATS 2017 and 2018. There exist 431 samples (both HGG and LGG) in the Dataset-2017 and 476 samples in the Dataset-2018. Both the datasets contain 146 training samples. 146 and 191 testing samples are present in Datasets 2017 and 2018 respectively. Sample images from Datasets BRATS 2017 and 2018 are presented in **Figure 4**.

4.2. Performance measures

The definition of evaluation metrics is presented in **Table 2**.

Table 2. Performance Metrics used.

Metrics used	Definition
Accuracy	$Ac_r = \frac{TP+TN}{TP+TN+FP+FN} \times 100$
Sensitivity	$Sensitivity = \frac{TP}{TP+FN}$
Specificity	$\text{Specificity} = \frac{\text{TN}}{(\text{FP}+\text{TN})}$
DSC	$DSC = \frac{2 \times TP}{FP+(2 \times TP)+FN}$

*TP→ TruePositive, FP → FalsePositive, FN → FalseNegative, TN → TrueNegative.

4.3. Result

The segmentation results of proposed work for the Dataset BRATS 2018 are given in **Figure 5**. Those results closely match the ground truth segmentation results.

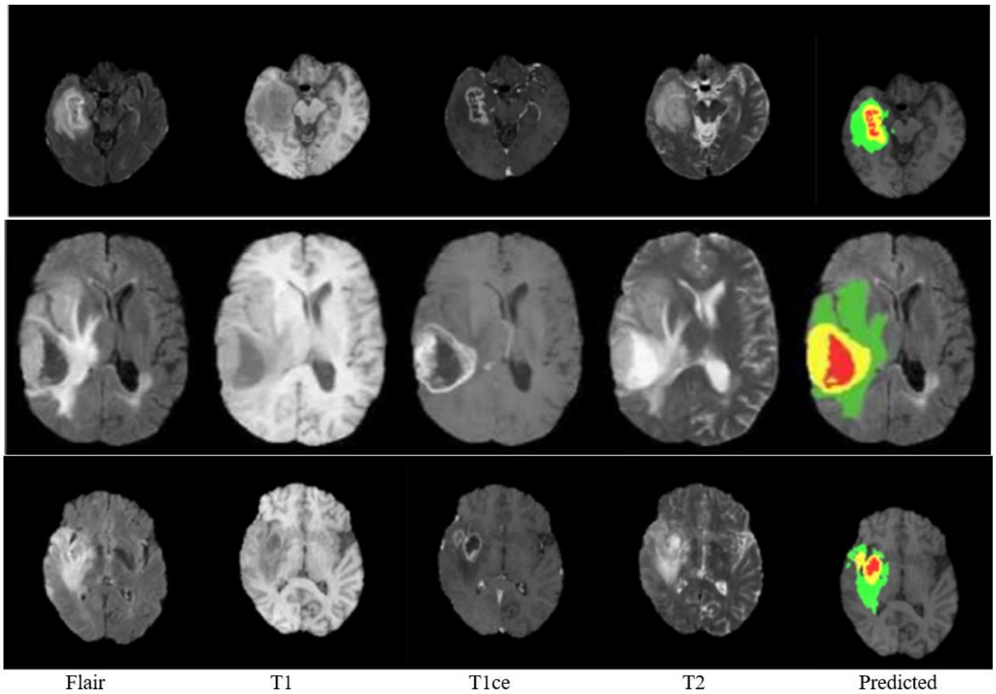

Figure 5. Predicted Segmentation Results of Proposed Work (Red → necrosis and non-enhancing, green → edema, and yellow → enhancing tumor).

The proposed method is tested on both datasets, and the results are presented in **Table 3**.

Table 3. Evaluation of the proposed work.

Measure	BRATS 2017	BRATS 2018
DSC	87.1	99.2
Sensitivity	86.4	100
Specificity	86	99
Accuracy	84.52	99.3

Table 3 shows that the results obtained by the proposed method for the Dataset BRATS 2018 are more significant than the Dataset 2017. For Dataset BRATS 2017, all the results are in the range of 99%–100%. For the Dataset 2018, the results range from 84%–87%.

4.4. Comparing proposed work with recent works

The proposed methods' results are compared with those discussed in Section 2. **Table 4** compares the DSC of the suggested method for the dataset BRATS 2017 with current methods.

Table 4. Comparing proposed method against recent methods for BRATS 2017 Dataset using DSC.

Method	Year	Dice core
Zhang et al.[12]	2021	82.8
Pereira et al.[13]	2019	80.9
Rehman et al.[14]	2021	81.17
PSPNet[15]	2019	68.8
Punn et al.[16]	2020	86.67
Dense 3D CNN[17]	2019	78.67
Proposed method	-	87.1

The inference from **Table 4** is that, the DSC of the proposed method (87.1% DSC) is drastically greater than Punn et al.'s[16] method (86.67% DSC). The sensitivity and DSC obtained by the suggested method for the Dataset BRATS 2018 are compared with some current methods in **Table 5**.

Table 5. Comparing proposed method with recent methods on BRATS 2018.

Method	Year	sensitivity	DiceScore
Zhou et al.[10]	2021	78.7	82.5
Ranjbarzadeh et al.[17]	2019	94.38	90.14
Chen et al.[18]	2020	86.67	80
Zhang et al.[19]	2020	-	83.4
Sharif et al.[20]	2021	100	98
Zhuge et al.[21]	2020	94	-
Narmatha et al.[22]	2020	95	-
Proposed method	-	100	99.2

In BRATS 2018 also, the proposed method reached maximum sensitivity value. The DSC value is also increased by 1.2% compared to the work of Sharif et al.[20].

4.5. Analysis of proposed work

The analysis of proposed work is done by studying the impact of residual neural networks and salient object detection. The residual neural network is analysed based on DSC, sensitivity, specificity, and accuracy. The salient object detection is analysed regarding computation time and the above mentioned metrics.

4.5.1. Impact of UNet and residual neural network

The advantage of using Res2UNet is studied by comparing it with UNet, 3D UNet, and 3DRes3UNet. Even though three dimensions have several advantages over two, the 2D UNet is also tested because it is the base network for 3DRes2Unet architecture. Finally, SOD is added, the obtained results on two datasets are reported in **Tables 6** and **7**.

Table 6. Impact of UNet, residual neural networks, and SOD on BRATS 2017 Dataset.

Network	DSC	Sensitivity	Specificity	Accuracy
UNet	83.24	82.86	82.36	82.45
3D UNet	85.34	84.5	83.9	83.14
3DRes2UNet	86.16	85	85.4	84
SOD + 3DRes2UNet	87.1	86.4	86	84.52

Table 7. Impact of UNet, residual neural networks, and SOD on BRATS 2018 Dataset.

Network	DSC	Sensitivity	Specificity	Accuracy
U Net	97.24	97.76	97.21	97.8
3D UNet	98.78	98.35	97.45	98
3DRes2UNet	99	99	98	98.5
SOD + 3DRes2UNet	99.2	100	99	99.3

Focussing the performance metric, accuracy, it is inferred from **Table 6** that the UNet model offers 82.45%, the 3D Unet provides 83.14 %, 3DRes2Unet gives 84% and 84.52 % accuracy is obtained in 3DRes2Unet after adding the SOD module on BRATS 2017 Dataset. All the models provide more than 97% accuracy on BRATS 2018 dataset but the proposed model has the highest accuracy of 99.3% based on **Table 7**. It is perceived that the 3D UNet has better results compared to 2D UNet. When the residual network is integrated with 3D UNet, it outperforms both methods. Finally, the results are above 99% when salient objects are used.

4.5.2. Impact of salient objects over computation time

The primary purpose of integrating SOD in the proposed method is to reduce the dimension of the 3D image. Thereby the execution time will be reduced. Hence the computation time is calculated for the proposed method with and without SOD. The method is tested using hardware, Intel Core i7 2.8 GHz having a GPU, NVIDIA GeForce GTX 1050. The execution time is compared in the chart given in **Figure 6**.

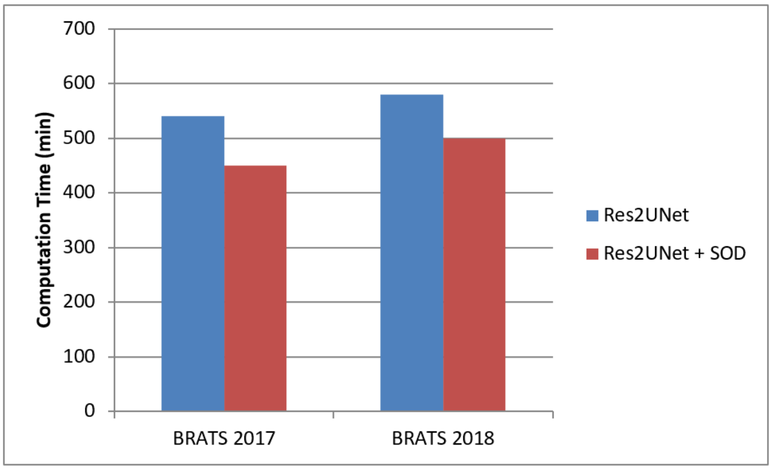

Figure 6. Computation time comparison of proposed method.

From **Figure 6**, it is inferred that the computation time is reduced by 16.67% for the dataset BRATS 2017 and 13.79% for the dataset BRATS 2018 after pre-processing the input using SOD algorithm.

5. Conclusion

Automatic segmentation of brain tumor is one of the vital researches in the medical advancement field. This paper proposed to use an improved version of UNet (3DRes2UNet) by combining salient object detection. The 3DRes2UNet accurately segments the tumor, and the SOD method reduces the computation overhead of the proposed method. Finally, the segmented tumor is classified using a multiclass SVM classifier. The proposed method is evaluated using BRATS 2017 and 2018 datasets. It outperforms other recent methods by achieving 87.1% DSC associated with dataset BRATS 2017 and 99.2% DSC regarding dataset BRATS 2018. The computation time is also reduced by 16.67% and 13.79% for BRATS 2017 and 2018, respectively. Further, the proposed method can be tested on the latest datasets also. This work used the salient object detection method to reduce the input size other pre-processing methods can be used along with the combined res2Unet module as a future enhancement.

Author contributions

Conceptualization, DM and UV; methodology, DM; software, NJ; validation, DM, NJ and KG; formal analysis, UV; investigation, DM; resources, NJ; data curation, DM; writing—original draft preparation, UV; writing—review and editing, NJ; visualization, UV; supervision, KG; project administration, NJ; funding acquisition, DM. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

1. Wang G, Li W, Ourselin S, et al. Automatic Brain Tumor Segmentation Based on Cascaded Convolutional Neural Networks with Uncertainty Estimation. Frontiers in Computational Neuroscience. 2019, 13. doi: 10.3389/fncom.2019.00056
2. Xu H, Xie H, Liu Y, et al. Deep cascaded attention network for multi-task brain tumor segmentation. In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer; 2019. pp. 420–428.
3. Thaha MM, Kumar KP, Murugan BS, Dhanasekeran S, Vijayakarthick P, Selvi AS. Brain tumor segmentation using convolutional neural networks in MRI images. Journal of medical systems. 2019; 43:1-0.
4. Hu Y, Liu X, Wen X, et al. Brain Tumor Segmentation on Multimodal MR Imaging Using Multi-level Upsampling in Decoder. Lecture Notes in Computer Science. Published online 2019: 168-177. doi: 10.1007/978-3-030-11726-9_15
5. Tuan TA, Tuan TA, Bao PT. Brain Tumor Segmentation Using Bit-plane and UNET. Lecture Notes in Computer Science. Published online 2019: 466-475. doi: 10.1007/978-3-030-11726-9_41
6. Weninger L, Rippel O, Koppers S, et al. Segmentation of Brain Tumors and Patient Survival Prediction: Methods for the BraTS 2018 Challenge. Lecture Notes in Computer Science. Published online 2019: 3-12. doi: 10.1007/978-3-030-11726-9_1
7. Hu X, Li H, Zhao Y, et al. Hierarchical Multi-class Segmentation of Glioma Images Using Networks with Multi-level Activation Function. Lecture Notes in Computer Science. Published online 2019: 116-127. doi: 10.1007/978-3-030-11726-9_11
8. Serrano-Rubio JP, Everson R. Brain Tumour Segmentation Method Based on Supervoxels and Sparse Dictionaries. Lecture Notes in Computer Science. Published online 2019: 210-221. doi: 10.1007/978-3-030-11726-9_19
9. Miller KD, Ostrom QT, Kruchko C, et al. Brain and other central nervous system tumor statistics, 2021. CA: A Cancer Journal for Clinicians. 2021, 71(5): 381-406. doi: 10.3322/caac.21693
10. Zhou T, Canu S, Vera P, et al. Latent Correlation Representation Learning for Brain Tumor Segmentation with Missing MRI Modalities. IEEE Transactions on Image Processing. 2021, 30: 4263-4274. doi: 10.1109/tip.2021.3070752

11. Zhang D, Huang G, Zhang Q, et al. Cross-modality deep feature learning for brain tumor segmentation. Pattern Recognition. 2021, 110: 107562. doi: 10.1016/j.patcog.2020.107562
12. Pereira S, Pinto A, Amorim J, et al. Adaptive Feature Recombination and Recalibration for Semantic Segmentation with Fully Convolutional Networks. IEEE Transactions on Medical Imaging. 2019, 38(12): 2914-2925. doi: 10.1109/tmi.2019.2918096
13. Rehman MU, Cho S, Kim J, et al. BrainSeg-Net: Brain Tumor MR Image Segmentation via Enhanced Encoder–Decoder Network. Diagnostics. 2021, 11(2): 169. doi: 10.3390/diagnostics11020169
14. Li H, Li A, Wang M. A novel end-to-end brain tumor segmentation method using improved fully convolutional networks. Computers in Biology and Medicine. 2019, 108: 150-160. doi: 10.1016/j.compbiomed.2019.03.014
15. Punn NS, Agarwal S. Multi-modality encoded fusion with 3D inception U-net and decoder model for brain tumor segmentation. Multimedia Tools and Applications. 2020, 80(20): 30305-30320. doi: 10.1007/s11042-020-09271-0
16. Chen C, Liu X, Ding M, et al. 3D Dilated Multi-fiber Network for Real-Time Brain Tumor Segmentation in MRI. Medical Image Computing and Computer Assisted Intervention—MICCAI 2019. Published online 2019: 184-192. doi: 10.1007/978-3-030-32248-9_21
17. Ranjbarzadeh R, Bagherian Kasgari A, Jafarzadeh Ghoushchi S, et al. Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. Scientific Reports. 2021, 11(1). doi: 10.1038/s41598-021-90428-8
18. Chen G, Li Q, Shi F, et al. RFDCR: Automated brain lesion segmentation using cascaded random forests with dense conditional random fields. NeuroImage. 2020, 211: 116620. doi: 10.1016/j.neuroimage.2020.116620
19. Zhang D, Huang G, Zhang Q, et al. Exploring Task Structure for Brain Tumor Segmentation from Multi-Modality MR Images. IEEE Transactions on Image Processing. 2020, 29: 9032-9043. doi: 10.1109/tip.2020.3023609
20. Sharif MI, Li JP, Amin J, et al. An improved framework for brain tumor analysis using MRI based on YOLOv2 and convolutional neural network. Complex & Intelligent Systems. 2021, 7(4): 2023-2036. doi: 10.1007/s40747-021-00310-3
21. Zhuge Y, Ning H, Mathen P, et al. Automated glioma grading on conventional MRI images using deep convolutional neural networks. Medical Physics. 2020, 47(7): 3044-3053. doi: 10.1002/mp.14168
22. Narmatha C, Eljack SM, Tuka AARM, et al. A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images. Journal of Ambient Intelligence and Humanized Computing. Published online August 14, 2020. doi: 10.1007/s12652-020-02470-5
23. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. Medical Image Computing and Computer-Assisted Intervention—MICCAI 2015. Published online 2015: 234-241. doi: 10.1007/978-3-319-24574-4_28
24. Gupta AK, Seal A, Prasad M, et al. Salient Object Detection Techniques in Computer Vision—A Survey. Entropy. 2020, 22(10): 1174. doi: 10.3390/e22101174
25. Zhang J, Sclaroff S, Lin Z, et al. Unconstrained Salient Object Detection via Proposal Subset Optimization. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Published online June 2016. doi: 10.1109/cvpr.2016.618
26. Xiao Z, Liu B, Geng L, et al. Segmentation of Lung Nodules Using Improved 3D-UNet Neural Network. Symmetry. 2020, 12(11): 1787. doi: 10.3390/sym12111787
27. Gao SH, Cheng MM, Zhao K, et al. Res2Net: A New Multi-Scale Backbone Architecture. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2021, 43(2): 652-662. doi: 10.1109/tpami.2019.2938758