Frontiers in
BIOMEDICAL TECHNOLOGIES

Original Article

Differentiating Tumor and Edema in Brain Magnetic Resonance Images Using a Convolutional Neural Network

Aida Allahverdi [1], Siavash Akbarzadeh [1], Alireza Khorrami Moghaddam [2], Armin Allahverdy [2,*]

[1] Department of Computer, Faculty of Mechanics, Electrical Power and Computer, Science and Research Branch, Islamic Azad University, Tehran, Iran

[2] Department of Radiology, School of Allied Medical Sciences, Mazandaran University of Medical Sciences, Sari, Iran

Received: 07 April 2018

Accepted: 07 June 2018

ABSTRACT

Purpose: Glioblastoma is the most common subset of glioma with a high grade of mortality. Early diagnosis may cause better therapeutic interventionsand brain MRI shows a good performance on tumor localization. Since manual tumor localization is time-consuming, an automatic tumor segmentation is usually recommended. Convolutional Neural Network (CNN) has a wide range application for machine vision and visual recognition.

Materials and Methods: In this study, an automatic brain tumor segmentation based on a fully CNN is presented. This method has been used to localize and differentiate active tumors including high grade and low-grade from edema in multi-modal MRI containing T1 weighted, T1 enhanced, T2 weighted and FLAIR. For assessing the segmentation performance, a dataset was used and divided into train and test subset. Each image was investigated by sliding the window with different sizes contained 5, 10, 15, 20 and 25 pixels.

Results: The results showed that increasing the window size improves the segmentation performance in training phase. It had no significant effect on the segmentation performance in testing phase, therefore increasing the window size improved the learnig of the neural network. The training accuracy for the window with 5 pixels size was 81.6% and for the window with 25 pixels was 96.5%. The test accuracy for the window with 5 pixels size was 80.5% and for the window with 25 pixels was 82.8%. Overall, the best segmentation performance of traning dataset was 97.6% and the best test segmentation performance was 89.7%.

Conclusion: The result with training dataset shows that increasing the sliding windows size may cause the increment of accuracy, but this increment may not necessarily increase the accuracy of test dataset.

Keywords:

Magnetic Resonance Image;

Segmentation;

Convolutional Neural Network;

Glioblastoma.

1. Introduction

The rate of incidence in tumor brain is 265.5 per million for women and 223.7 per million for men [1]. Gliomas are the most common and aggressive brain tumors, this type of brain tumor has high mortality rate [2, 3]. This tumor has many subsets, but the most common type of gliomas is glioblastoma [4]. This type of tumor brain is very aggressive and its 5-year survival rate is about 5.3% [1]. Moreover, the treatment of this tumor is very expensive [5]. Therefore, the diagnosis of glioma is vital. The therapy planning is the most important stage of every treatment for glioblastoma. The first step of the therapy planning is an accurate localization of tumor in the brain and its differentiating from its neighbor tissue. Magnetic Resonance Images (MRI) is the most common technique for the visualization and localization of brain tumor [6]. Manual segmentation of tumor from other tissue

***Corresponding Author**:
Armin Allahverdy, PhD
Department of Radiology, School of Allied Medical Sciences, Mazandaran University of Medical Sciences, Sari, Iran
Tel: (+98)9113554959 .
Email: armin.allahverdy@gmail.com

is very time consuming and may be influenced by mistakes and localizing the glioma is so difficult [7]. The automatic segmentation of glioblastoma may be a helpful tool to decrease the tumor localization errors and glioblastoma is surrounded by edema tissue. In heterogeneous tumors, like gliomas, this distinction cannot be made with conventional MRI techniques. Therefore, the most likely assignment for this abnormal tissue is low grade glioma. Low grade tumor next to glioblastoma is pathologically possible. In this study, we decided to segment the edema and tumor tissue using MRI images.

There are many approaches to tissue segmentation in MRI like region-based and contour based approaches [8, 9]. Convolutional Neural Networks (CNN) show a better performance to automated segmentation of the images based on region-based approach in the sense of accuracy and sensitivity of tissue localization [10].

Recently, there is growing interest in using CNN to classify the images using CNNs[11]. This huge interest is influenced by the efficiency of CNN for image classification [12]. In 2012, the CNN was used for the classification of neurons into a membrane and non-membrane pixels in microscopic images [13]. Moreover, many studies were applied to segment the brain MRI using CNN [3]. These studies may be based on individual slice segmentation [8] or volumetric segmentation [14] and these networks may be hybrid by statistical methods [10].

In this study, we will investigate the performance of the convolutional neural network for segmentation and localization of edema and glioblastoma in multimodal magnetic resonance images of the brain.

2. Materials and Methods

2.1. Dataset

As in this study, the MRI image will be investigated for tumor and edema tissue segmentation, we used multi-parametric MRI of MICCAI BraTS challenge dataset, which contained T1, T1 Gadolinium (Gd) enhanced, T2 and FLAIR as illustrated in Figure 1.

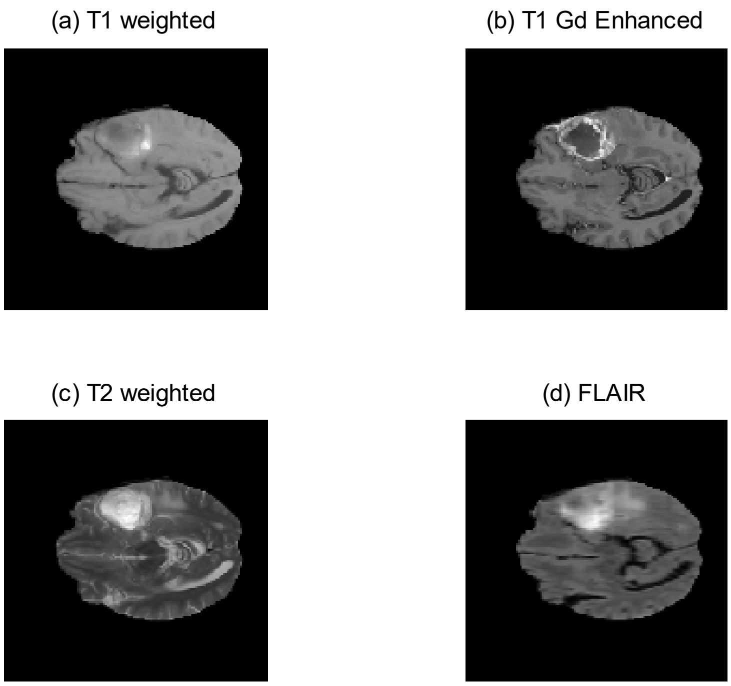

Figure 1. The multi-parametric brain MRI (a, b, c, d)

This dataset includes 15 high-grade and 15 low-grade simulated brain tumor images. The high-grade patients are patients which have less than two years life expectancy and low-grade patients have several years life expectancy. Each image has 155 slices and 240×240 dimensions. For each slice an expert annotation for “active tumor” and “edema” is provided as illustrated in Figure 2. The dataset has been divided into training dataset (25 subjects) and test dataset (5 subjects).

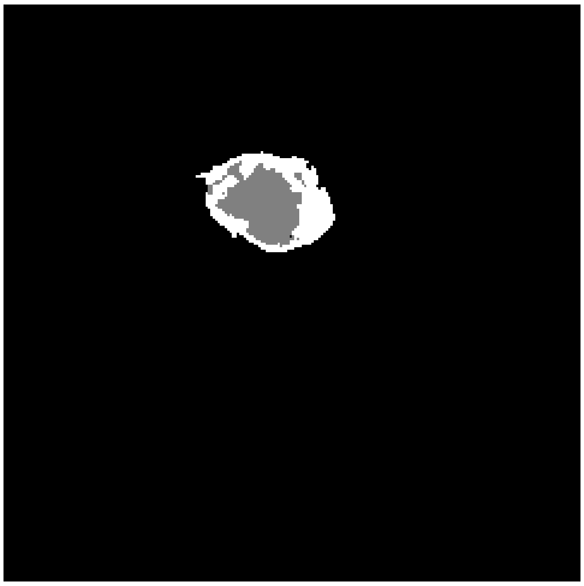

Figure 2. Expert annotation for active tumor and edema

2.2. Fully Convolutional Neural Network

Structure

The implemented CNN has a fourth order input tensor , where n^3 is the image dimension and C is channeling per voxel. As in this study, 4 contrasts of MRI will be used, then C is 4 in Figure 3 as each layer contains the different contrast of multi-parametric MRI and red square is the input image with n^3 dimension. The inputs of the neural network are sliding windows pixels of each multi-parametric MRI. For example, the input of neural network with 5 pixels sliding windows contains 25 pixels of T1 wieghted, T1 Gd enhanced, T weighted and FLAIR. Therefore, this network feed 100 pixels as input. The output has K states, for as much as the aim of this study is clustering the image into the tumor and edema tissue, the K will be 2. This states were clarified by radiologists and are showed as images corresponding to each slide.

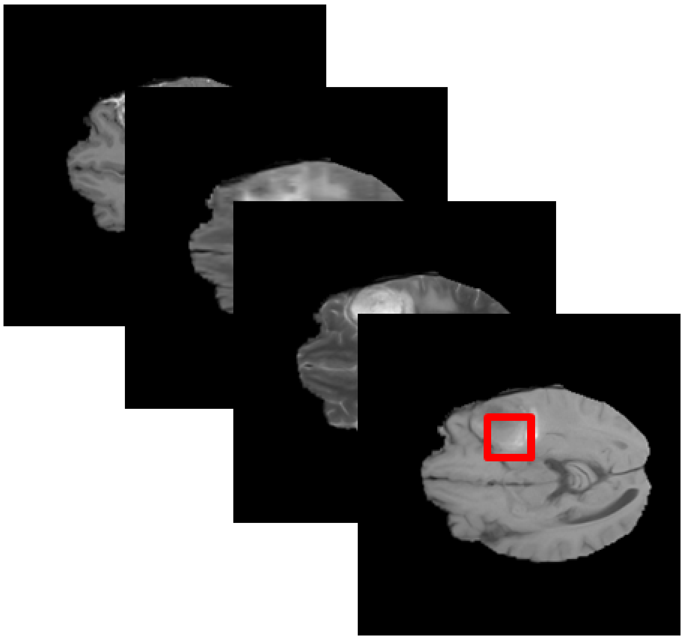

Figure 3. The structure of fully convolutional neural network input

The Fully Convolutional Neural Network (FCNN) takes the n^3 patch of pixels as the input and presents the n^3 segmented volume as the output. This network consists of two 3D convolution and two deconvolution layers. The convolution layers are followed by the ReLU activation function, dropout, batch normalization, and 2×2 max-pooling. The deconvolution layers are followed by ReLU activations and batch-normalization. This model uses softmax cross-entropy loss with L2 regularization and is trained using Adam optimization. The model architecture with n=24 as an example is shown in Figure 4.

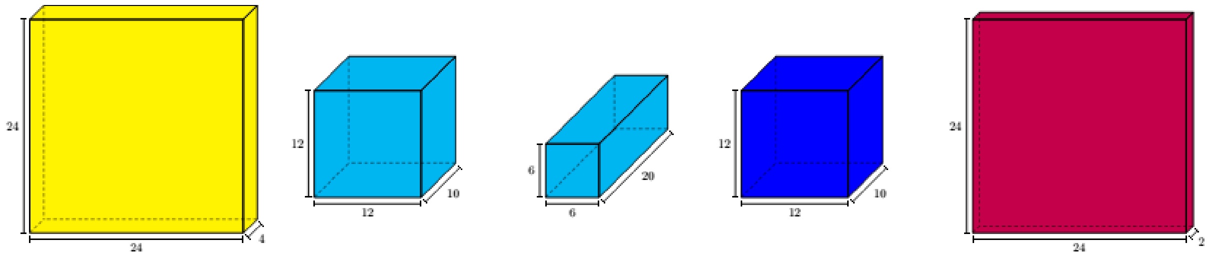

Figure 4. Fully convolutional neural network structure with n=24 [15]

3. Results

As mentioned before, the aim of this study is segmenting brain MRI into edema and tumor tissue using the fully convolutional neural network. Therefore, for evaluating this approach, the measures of accuracy, sensitivity and specificity as Equations 1 to 3.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

Where TP is a true positive, TN is a true negative, FP is a false positive and FN is a false negative. In these terms, positive means edema and negative means tumor.

For more investigations, the sliding window with dimensions 5, 10, 15, 20 and 25 was used as an input tensor of the fully convolutional neural network. In Figure 5, an example result of a fully convolutional neural network for train dataset with a sliding window at dimension 10 is illustrated and in Figure 6, the same result showed for the test dataset.

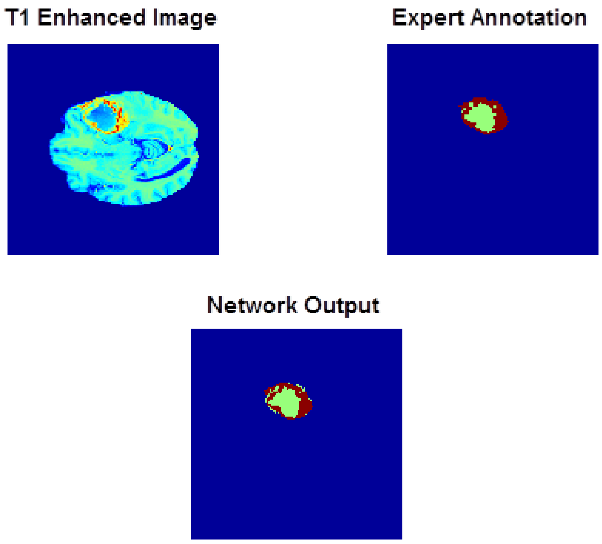

Figure 5. A result of a fully convolutional neural network for train dataset

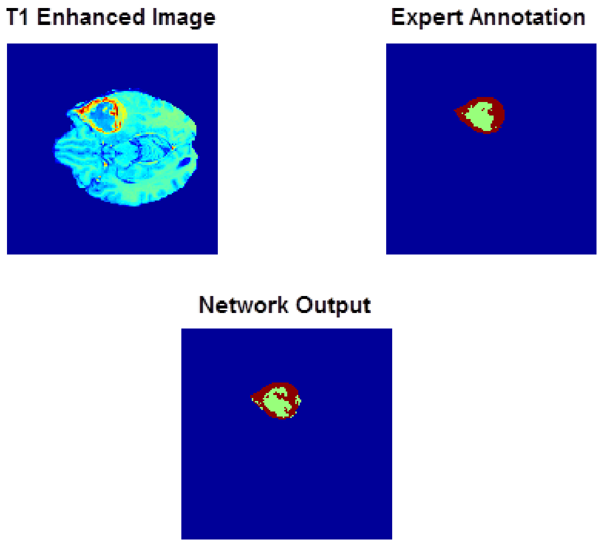

Figure 6. A result of a fully convolutional neural network for test dataset

In Chart 1 the accuracy, sensitivity and specificity of this segmentation for train dataset are shown for a different dimension of the sliding window. As it is obvious from Figure 7, there is a significant increment in precision measures with increasing the dimension of the sliding window. Also, these precision measures for the test dataset have been illustrated in Figure 8. Moreover, the average and standard deviation of training and test accuracy are illustrated in Table 1.

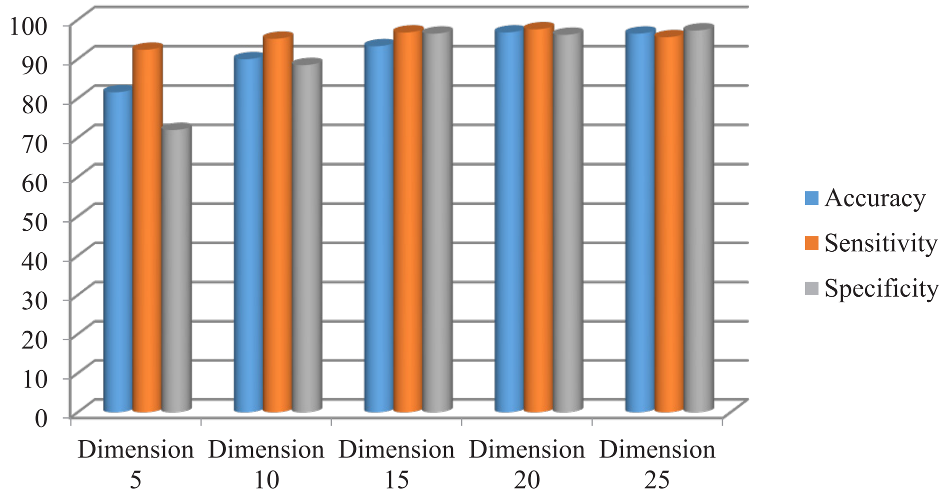

Figure 7. Accuracy, sensitivity and specificity of the segmentation for train dataset

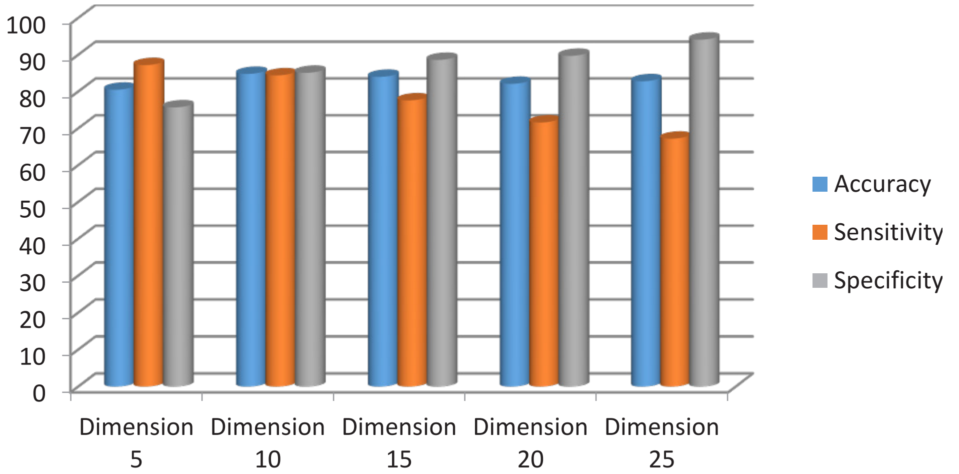

Figure 8. Accuracy, sensitivity and specificity of the segmentation for the test dataset

Table 1. Average and standard deviation of training and test accuracy

	Dimension 5	Dimension 10	Dimension 15	Dimension 20	Dimension 25
Trainig Accuracy	81.6±1.2	90±1.7	93.3±0.9	96.8±1.8	96.5±1.4
Test Accuracy	80.5±1.2	84.8±1.3	84±1	82.1±1.1	82.8±1.2

The Figure 8 shows that the more increment of sliding windows dimension can not necessarily increase the accuracy, because increasing the sliding window's dimension may cause the over learning the fully convolutional neural network.

4. Conclusion

In this study, a new automatic tumor segmentation based on a convolutional neural network has been introduced. This neural network catches n^3 dimension voxels as the input and presents n^3 segmented voxels as the output. The differentiating the tumor and edema was the aim of this segmentation. The used dataset has been divided into training and test dataset which training dataset consists of 25 subjects and test datasets consist of 5 subjects. For test and training the network, different sizes of the sliding window contain 5, 10, 15, 20 and 25 pixels has been considered. The result with training dataset shows that increasing the sliding windows size may cause the increment of accuracy, but this increment may not necessarily increase the accuracy of the test dataset. These variations have been illustrated in Figure 9.

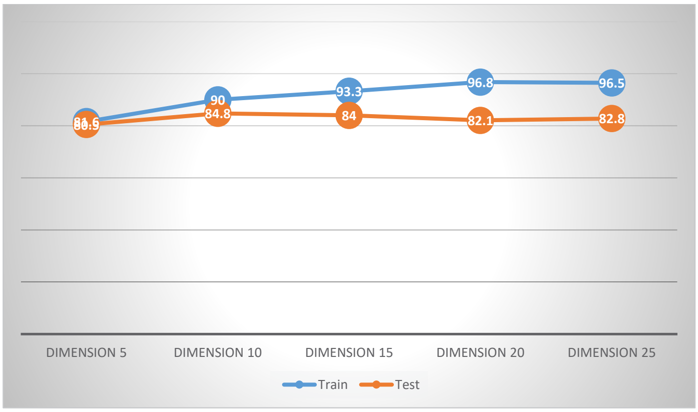

Figure 9. Comparing the variation of training and test accuracy

As the Figure 9 shows, the increment of sliding window size has no effect on the test accuracy but it causes the increment of training accuracy, which may cause the over learning of neural network.

References

1- B. A. Kohler *et al.*, “Annual report to the nation on the status of cancer, 1975–2007, featuring tumors of the brain and other nervous system,” *Journal of the national cancer institute,* vol. 103, no. 9, pp. 714-736, 2011.

2- E. C. Holland, “Progenitor cells and glioma formation,” *Current opinion in neurology,* vol. 14, no. 6, pp. 683-688, 2001.

3- B. H. Menze *et al.*, “The multimodal brain tumor image segmentation benchmark (BRATS),” *IEEE transactions on medical imaging,* vol. 34, no. 10, pp. 1993-2024, 2015.

4- K. Urbańska, J. Sokołowska, M. Szmidt, and P. Sysa, “Glioblastoma multiforme–an overview,” *Contemporary oncology,* vol. 18, no. 5, p. 307, 2014.

5- S. Ray, M. M. Bonafede, and N. A. Mohile, “Treatment patterns, survival, and healthcare costs of patients with malignant gliomas in a large US commercially insured population,” *American health & drug benefits,* vol. 7, no. 3, p. 140, 2014.

6- L. Ghorbanzadeh and A. E. Torshabi, “An Investigation into the Performance of Adaptive Neuro-Fuzzy Inference System for Brain Tumor Delineation Using ExpectationMaximization Cluster Method; a Feasibility Study,” *Frontiers in Biomedical Technologies,* vol. 3, no. 1-2, pp. 8-19, 2017.

7- M. Havaei *et al.*, “Brain tumor segmentation with deep neural networks,” *Medical image analysis,* vol. 35, pp. 18-31, 2017.

8- T. Kapur, W. Eric, L. Grimson, R. Kikinis, and W. M. Wells, “Enhanced spatial priors for segmentation of magnetic resonance imagery,” in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 1998, pp. 457-468: Springer.

9- E. Bullmore *et al.*, “Computerized brain tissue classification of magnetic resonance images: a new approach to the problem of partial volume artifact,” *Neuroimage,* vol. 2, no. 2, pp. 133-147, 1995.

10- K. Kamnitsas *et al.*, “Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation,” *Medical image analysis,* vol. 36, pp. 61-78, 2017.

11- A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in neural information processing systems*, 2012, pp. 1097-1105.

12- B. Kayalibay, G. Jensen, and P. van der Smagt, “CNN-based segmentation of medical imaging data,” *arXiv preprint arXiv:1701.03056,* 2017.

13- D. Ciresan, A. Giusti, L. M. Gambardella, and J. Schmidhuber, “Deep neural networks segment neuronal membranes in electron microscopy images,” in *Advances in neural information processing systems*, 2012, pp. 2843-2851.

14- H. Chen, Q. Dou, L. Yu, and P.-A. Heng, “Voxresnet: Deep voxelwise residual networks for volumetric brain segmentation,” *arXiv preprint arXiv:1608.05895,* 2016.

15- L. Shen and T. Anderson, “Multimodal Brain MRI Tumor Segmentation via Convolutional Neural Networks.”