DOES CONTEXTUAL INFORMATION IMPROVE 3D U-NET BASED
BRAIN TUMOR SEGMENTATION?

Iulian Emil Tampu¹, Neda Haj-Hosseini¹, Anders Eklund¹,²,³

¹Department of Biomedical Engineering
²Division of Statistics & Machine Learning, Department of Computer and Information Science
³Center for Medical Image Science and Visualization (CMIV)
Linköping University, Sweden

ABSTRACT
Effective, robust and automatic tools for brain tumor segmen-
tation are needed for extraction of information useful in treat-
ment planning. In recent years, convolutional neural networks
have shown state-of-the-art performance in the identification
of tumor regions in magnetic resonance (MR) images. A large
portion of the current research is devoted to the development
of new network architectures to improve segmentation accu-
ricy. In this work it is instead investigated if the addition
of contextual information in the form of white matter (WM),
grey matter (GM) and cerebrospinal fluid (CSF) masks im-
proves U-Net based brain tumor segmentation. The BraTS
2020 dataset was used to train and test a standard 3D U-Net
model that, in addition to the conventional MR image modal-
ities, used the contextual information as extra channels. For
comparison, a baseline model that only used the conventional
MR image modalities was also trained. Dice scores of 80.76
and 79.58 were obtained for the baseline and the contextual
information models, respectively. Results show that there is
no statistically significant difference when comparing Dice
scores of the two models on the test dataset \( p > 0.5 \). In
conclusion, there is no improvement in segmentation perform-
ance when using contextual information as extra channels.

Index Terms— Brain tumor, automatic segmentation, 3D
U-Net, deep learning, artificial intelligence

1. INTRODUCTION
Generally, patients diagnosed with brain tumor undergo rad-
tical treatment which includes surgical tumor resection fol-
lowed by radiotherapy and concomitant chemotherapy [1].
A major factor that influences patient survival and post-
operative morbidity is the extent of the treatment region
[1, 2]. Treatment planning depends extensively on diagnostic
radiology images for the identification of the tumor, a key in-
formation for balancing the extent of the treatment target with
the collateral effects. MRI modalities such as T1-weighted,
T1-weighted with post-contrast gadolinium enhancement
(T1Gd), T2-weighted and T2 fluid attenuated inversion re-
covery (T2-FLAIR) are commonly used for the identification
of the tumor. Reliable tools for the extraction of relevant
information from MR images are needed. Manual segmen-
tation of brain tumors is commonly practiced in clinical routine
[3], however, this is a time consuming and labor-intensive
task. Moreover, manual annotation is not objective, with poor
agreement between specialists [4]. Automatic methods could
overcome these limitations providing a faster and objective
identification of the tumor subregions. Automatic segmen-
tation of brain tumor structures in MR images is challenging
and has attracted a great research interest. Among the pro-
posed methods [5], convolutional neural networks (CNNs)
have shown state-of-the-art performance, ranking first in the
Multimodal Brain Tumor Image Segmentation Benchmark
(BraTS) challenge during recent years. Given the automatic
feature extraction of CNNs [6], the majority of the research
is focused on designing more efficient network architectures
for the segmentation task. One of the most popular CNN
architectures is U-Net [7], which introduces skip connections
between the layers in the network. A plethora of U-Net-like
architectures were developed, including among others, labori-
ous skip connections strategies [8] and attention mechanisms
[9]. Isensee et. al [10] showed that improving segmentation
performance is not only a matter of adjusting the network ar-
chitecture, by obtaining top performance using a well-trained
U-Net. The choice of loss function, training strategy and
post-processing showed to have an impact on the segmenta-
tion performance. Another approach is to provide the network
with more information. In two studies Shen H. et al. [11, 12]
added four input channels to their fully convolutional net-
work in addition to the four MR modalities. The additional
information were symmetry maps computed on all the MR
modalities describing the asymmetry between the brain hemi-
spheres introduced by the tumor. A marginal improvement
of the segmentation performance was reported for the edema
region. The aim of this work was to expand on this line of
thought considering if the addition of contextual information
in the form of WM, GM and CSF masks to the conventional
2. MATERIALS AND METHODS

The BraTS 2020 dataset was used [13, 14, 15] that contains 369 pre-operative multimodal (T1, T1Gd, T2 and FLAIR) 3D MR images of both high grade glioma (HGG) (n = 293) and low grade glioma (LGG) (n = 79). Manual annotations of three tumor sub-regions for each patient are provided with the dataset identifying the necrotic (NCR) and the non-enhancing tumor core (NET), the enhancing tumor (ET) and the peritumoral edema tissue (ED). The combination of the above annotations, namely the tumor core (TC = NCR ∪ NET ∪ ET), the ET and the whole tumor (WT = TC ∪ ED) are targets of the segmentation task. A complete description of the BraTS 2020 dataset is available in [15]. Contextual information in form of WM, GM and CSF masks was obtained using FM-RIB’s automated segmentation tool (FAST) [16] applied on the individually intensity normalized and zero-centered T1-weighted MR volumes. The difference between the FAST masks obtained from the raw T1 and the intensity normalized and zero-centered T1 volumes was minor. Of the total 369 subjects, 92% showed less than 10% difference in voxel classification (WM, GM or CSF). The intensity normalized and zero-centered volumes were used instead of the raw data, since a preliminary investigation of the proposed method indicated that segmentation performance was lower when using contextual information from raw T1 data compared to when it was obtained from the intensity normalized and zero-centered volumes. Before training, 36 subjects were randomly selected as the test dataset, containing an equal number of HGGs and LGGs. The nnU-Net deep learning framework [17] was used instead of an in-house 3D U-Net to allow replication of the reported results. nnU-Net is built upon the 3D U-Net architecture and automatically tunes the network hyper-parameters based on the training dataset and hardware available. In particular, the 3D fullres nnU-Net configuration was used, and several Nvidia Tesla V100 GPUs (32 GB memory) were used for the training. During training, the sum of Dice and cross-entropy loss was minimized using the Adam optimizer. The number of training epochs was automatically set to 1000 by nnU-Net, without any early stopping strategies. To investigate if the addition of contextual information improves glioma segmentation performance, two models were trained that differ in the number of input channels: a baseline model (BLM) with 4 input channels using the four MRI modalities provided by BraTS, and a contextual information model (CIM) that in addition used the WM, GM and CSF masks from FAST, having a total of 7 input channels. The performance of the models was compared in terms of Dice score and 95% Hausdorff distance (HD) on the segmentation targets using a two-tailed t-test. Equality of the variances assumption was tested using F-test in the SPSS (IBM SPSS, Version 27.0. Armonk, NY: IBM Corp). Fig. 1 shows an overview of the method.

3. RESULTS

An example of contextual information can be seen in Fig. 1, where the cross-section of CSF, GM and WM masks obtained...
Table 1. Segmentation performance comparison between the baseline and contextual information models. Validation and test performances are given.

| Model | Validation Dice | 95% HD | Test Dice | 95% HD |
|-------|-----------------|--------|----------|--------|
|       | TC   | ET   | WT   | TC   | ET   | WT   | TC   | ET   | WT   |
| BLM   | 84.55 | 81.70 | 88.59 | 9.61 | 31.35 | 5.31 | 82.36 | 70.07 | 89.85 | 15.62 | 99.54 | 13.67 |
| CIM   | 84.47 | 77.94 | 88.45 | 15.19 | 36.99 | 11.1 | 81.95 | 67.11 | 89.67 | 15.90 | 98.72 | 13.78 |

using FAST are shown for one subject. By visually inspecting the FAST results, the contextual information is descriptive of the brain WM, GM and CSF structures, with the masks being distorted only in the regions where the tumor is located. Validation and testing results for both BLM and CIM, for all segmentation targets are summarized in Table 1. The mean Dice scores on the testing dataset is 80.76 and 79.58, for the baseline and contextual information models, respectively. When comparing the two models, there is no statistically significant difference ($p > 0.5$) in Dice score performance with respect to all segmentation tasks. No considerable difference was observed in the effect of the contextual information to the segmentation of LGG and HGG tumors when evaluated separately.

4. DISCUSSION AND CONCLUSION

When training a CNN for brain tumor segmentation, the addition of contextual information in the form of WM, GM and CSF masks shows no significant improvement when compared to a model trained only on conventional MRI modalities. One possible reason for this may be found in how the WM, GM and CSF masks are computed. FAST uses pixel intensity and spatial information for the segmentation. Arguably, this is very similar to what a U-Net architecture is using when trained for semantic segmentation. Thus, it is possible that the network is independently creating a representation of WM, GM and CSF at some stage during training from the conventional MRI modalities, nullifying the additional information. However, when providing WM, GM and CSF masks directly as input channels, the network may train faster since it does not have to learn this information. This was not tested here, since the absence of early stopping strategies in the nnUNet framework makes the comparison between training times of the two models not possible. Another reason may be found in the quality of the contextual information. As shown in Fig. 1, the WM, GM and CSF masks are distorted in the brain region containing the tumor, which may confuse the network. One possible way of refining the contextual information is to use a two-step approach: first, train a model on the conventional MRI images to segment the whole tumor region, then use this segmentation to refine the contextual information and use it to train a second network. Future research should address if the addition of different MR modalities or image-derived quantities improves brain tumor segmentation. For example, other MR modalities may provide information that is not already available in the conventional MR modalities. The major factor hindering such investigation at the current moment is the lack of a standardized dataset as BraTS which includes extra MR modalities. In conclusion, the addition of WM, GM and CSF masks as extra channels to the conventional MR image modalities shows not to improve tumor segmentation performance when using a 3D U-Net architecture.

5. COMPLIANCE WITH ETHICAL STANDARDS

This study was conducted using human subject data made available in open access by (BraTS) requiring only citation of the source references [13, 14, 15]. Ethical approval was not required according to the data usage agreement provided with the data.

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