Brain Tumor Segmentation Project

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Abstract

The following research endeavor this group is undertaking expands upon the development of a robust and adaptable brain tumor segmentation model, envisioned to be submitted to the *BraTs-ISBI 2024 - Generalizability Across Tumors* Challenge, a distinguished facet of the International Symposium on Biomedical Imaging (ISBI) workshop. The primary objective entails harnessing the dataset provided by the challenge to engineer a deep learning framework adept at proficiently executing brain tumor segmentation while demonstrating resilience across various MRI scanners, demographic variances, and diverse manifestations of cerebral lesions and tumors. The overarching aim of this challenge is to uphold relatively high accuracy throughout these multifaceted scenarios. After rigorous experimentation and evaluation, the outcomes substantiate the efficacy of the devised model, which exhibits notable performance across a spectrum of conditions, thereby underscoring its adaptability and utility in diverse clinical settings. This group's project code can be accessed from the following link: `https://colab.research.google.com/drive/1O5qiL8Y8bzsguOBU7NefhsEWa4ooV2hA?usp=sharing`.

1 Initial Approach and Proposal

The initial (Figure 1) inspiration for the approach stemmed from the research of Shelhamer et al., whose successful utilization of Fully Convolutional Neural Networks (FCNNs) for image segmentation provided a solid foundation for proper image segmentation. The initial strategy was to build a

Submitted to 38th Conference on Neural Information Processing Systems (NeurIPS 2024). Do not distribute.

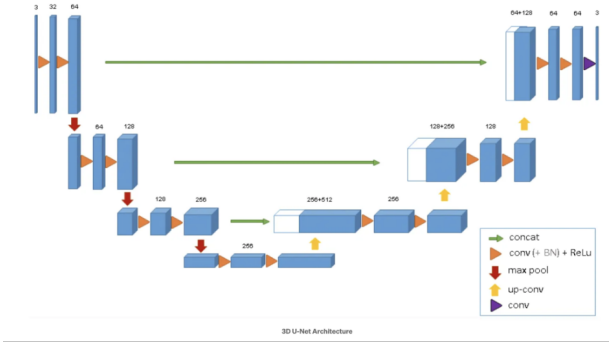

Figure 1: Initial UNet Architecture

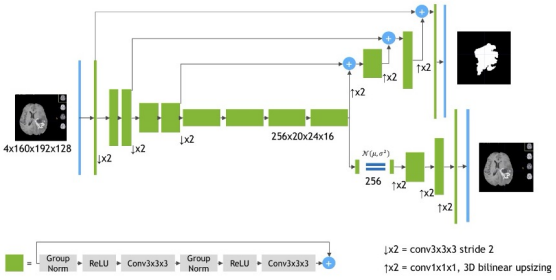

Figure 2: Current 3D SegResNet Architecture (pre-trained)

U-Net from a three-layer Convolutional Neural Network (CNN), incorporating Rectified Linear Unit (ReLU) activation functions and max-pooling operations between each layer within the architecture. However, upon examining the accuracies of this architecture, achieving further improvements in accuracy proved to be elusive compared to that of the referenced studies. Therefore an extremely computationally intensive architecture with a highly deep network was needed to reasonably train and get decent results.

Therefore, a new approach and proposal were discussed and examined which drew insights from the works of Yoganda et al. and Isensee et al. Their utilization of UNet architectures, specifically tailored for brain tumor segmentation, demonstrated promising outcomes. In pursuit of robust methodologies, the group encountered Monai, an open-source framework dedicated to Deep Learning in healthcare imaging, where they identified a SegResNet model pre-trained on BraTs 2018 data (Figure 2), demonstrating compatibility with their 3D dataset. Subsequently, this group leveraged the pre-trained model from Monai as their starting point, originally trained on BraTs 2018, and initiated a process of fine-tuning and retraining using data sourced from the original BraTs 2024 challenge. Despite the expansion in dataset size and diversity, they meticulously devised custom functions, including the DataSet and DataLoader functions, to ensure the seamless integration and processing of their data.

As mentioned previously, the primary objective is to develop a generalizable model capable of achieving a high DICE score, a metric indicative of segmentation accuracy while maintaining adaptability across diverse scenarios. Establishing a baseline target of attaining a DICE score of 0.85. This threshold is derived from an exhaustive examination of various other studies referenced throughout the project, most of which commonly reported DICE scores ranging from 0.85 to 0.9.

2 Motivation

The motivation driving this research challenge arises from the urgent need to promptly identify and treat brain tumors from MRI scans. Tumors can proliferate rapidly and pose significant health risks if left undetected. However, the manual identification of tumors from MRI scans is labor-intensive and

requires the expertise of specialized professionals, a resource that may be scarce. Furthermore, this group is deeply intrigued by the prospect of contributing to the realm of Computational Neuroscience through this project. The objective is to develop a model capable of effectively highlighting the presence and locations of tumors in MRI scan data. This advancement holds the potential to streamline the diagnostic process, enabling healthcare providers to promptly administer treatments, which will increase the number of patients receiving timely interventions.

By embarking on this project, the goal is not only to create a valuable tool for medical professionals but also to explore novel applications of deep learning architectures, particularly U-Nets and ResNets. Tailoring various machine learning architectures based on research will aid in enhancing precision and efficiency in tumor detection. Ultimately, the aim is to provide significant contributions to continuous research and innovation in medical image analysis, striving to enhance patient outcomes and propel advancements in neuroimaging.

3 Data Source

The data utilized in this study is sourced from the challenge associated with the workshop for brain tumor segmentation. In this case, all participants are strictly prohibited from incorporating external data sources for model training. Nevertheless, in the event of insufficient accuracy, the data is going to be sourced from previous *BraTs* datasets in order to enhance performance. The overarching aspiration is to develop a model capable of accommodating various types of brain tumor imaging, suggesting the potential benefit of incorporating a more diverse array of data. However, such expansion may be considered as a subsequent step following the successful implementation of the present project.

4 Related Work and Baseline

Several papers submitted to past *BraTs* challenges serve as valuable benchmarks for guiding the direction of the current research. They provide a baseline for target accuracy levels and suggest appropriate model architectures to consider for the current challenge.

4.1 BraTs 2017

The following report employs a 3D Dense UNet CNN for glioma segmentation, evaluated on the *BraTS* validation server and Oslo University Hospital's clinical dataset, reporting DICE scores for whole tumors, tumor cores, enhancing tumors, surrounding edema, and non-enhancing tumors including necrosis.

Bangalore Yogananda, C. G., Shah, B. R., Vejdani-Jahromi, M., Nalawade, S. S., Murugesan, G. K., Yu, F. F., Pinho, M. C., Wagner, B. C., Emblem, K. E., Bjørnerud, A., Fei, B., Madhuranthakam, A. J., Maldjian, J. A.(2020, June). *A fully automated deep learning network for Brain Tumor Segmentation.* Tomography (Ann Arbor, Mich.). `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7289260/`

Another approach leveraged data from the past *BraTs* 2013 challenge, utilizing Convolutional Neural Networks (CNNs) to learn task-specific feature hierarchies from diverse MRI modalities for brain tumor segmentation. The study evaluates various CNN architectures using the fully-annotated MICCAI *BraTs* challenge 2013 dataset to quantitatively compare their performance.

Papers with Code. *Brain Tumor Segmentation with Deep Neural Networks*. Papers With Code. (n.d.). `https://paperswithcode.com/paper/brain-tumor-segmentation-with-deep-neural`

Similar to the previous studies, this research utilizes MR sequences, like T1-weighted and T2-weighted images, for brain tumor segmentation and employs a cascade of CNNs to sequentially segment tumor subregions.

Papers with Code. *Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks*. Papers With Code. (n.d.). `https://paperswithcode.com/paper/automatic-brain-tumor-segmentation-using-1`

4.2 BraTs 2018

The study introduces a semantic segmentation network with an encoder-decoder architecture for automating brain tumor segmentation from 3D MRIs, including a variational auto-encoder branch to optimize performance, as demonstrated by its first-place ranking in the BraTS 2018 challenge.

Papers with Code. *3D MRI brain tumor segmentation using auto-encoder regularization*. Papers With Code. (2018). https://paperswithcode.com/paper/3d-mri-brain-tumor-segmentation-using/review/

4.3 BraTs 2020

In challenges from the recent past, the following research introduces a two-stage encoder-decoder model with variational autoencoder regularization for brain tumor subregional segmentation, incorporating attention gates and expanded dataset training in the second stage.

Papers with Code. *3A Two-Stage Cascade Model with Variational Autoencoders and Attention Gates for MRI Brain Tumor Segmentation*. Papers With Code. (2020). https://paperswithcode.com/paper/a-two-stage-cascade-model-with-variational

In a slightly different fashion, this study applies nnU-Net (No New U-Net) to the BraTS 2020 challenge, achieving notable results by enhancing the baseline configuration through BraTS-specific modifications

Papers with Code. *nnU-Net for Brain Tumor Segmentation*. Papers With Code. (2020). https://paperswithcode.com/paper/nnu-net-for-brain-tumor-segmentation

4.4 BraTs 2023

Another research study extends to the examination of last year's BraTS 2023 challenge, incorporating a model pre-trained on datasets from previous iterations, specifically BraTS 2020 and BraTS 2021. This pre-training strategy underscores a commitment to leveraging historical data for enhanced performance.

faizan1234567. (2024). FAIZAN1234567/Brats23-tumors-segmentation: Brain tumors segmentation on 3D MRI images. GitHub. https://github.com/faizan1234567/BraTS23-Tumors-Segmentation

5 Results

During experimentation, the DiceLoss function was employed as the chosen loss function, alongside the utilization of the Dice Score metric to assess the accuracy of our model's predictions.

Upon fine-tuning the pre-trained model for a span of 5 epochs to obtain preliminary results, a notable improvement was observed in performance.

Each row in the dataset represents a distinct channel, with each channel delineating different segments of the tumor. As it can be seen in the first row of Figure 3, the inputs involve 3D MRI Scans of the brain. In the second row of Figure 3, the masks are applied from the group's own data loader for the 3D scans. The pre-trained models are effectively utilized as can be seen through the prediction in the third row of Figure 3.

Additionally, the accompanying accuracy and loss plots (Figure 4 and Figure 5) for the training and validation sets show noteworthy results even though there are some instances of overfitting. However, the current model performs in a much computationally intensive environment making the results that much more impressive.

It is noteworthy to mention that due to the computational intensity inherent in both the dataset and model architecture, the training process consumed approximately 7 hours to complete just around 5 epochs, with a batch size of 2. This extended duration is primarily attributed to the intricate nature of processing 3D images.

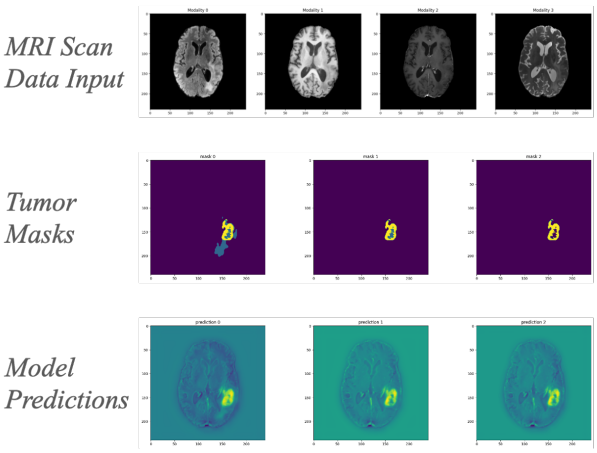

Figure 3: Results with Inputs, Masks, and Predictions

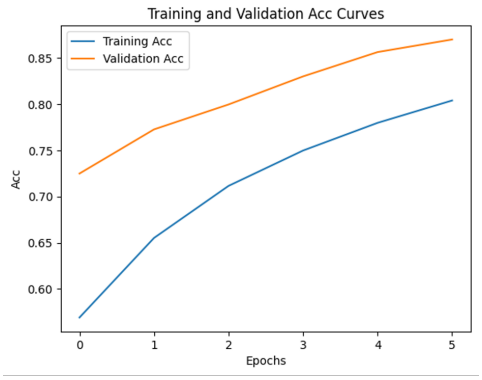

Figure 4: Training/Validation Accuracy Plot

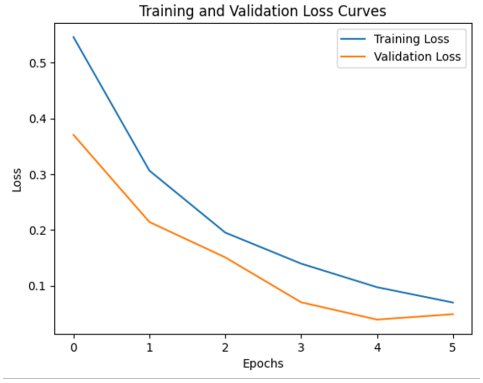

Figure 5: Training/Validation Loss Plot

6 Evaluation Protocols

After thorough research and careful consideration, this group opted to employ the DICE score and Hausdorff distance metrics for evaluation. The DICE score assesses pixel-level similarity between the predicted segmented image and the ground truth, with values ranging from 0 to 1 indicating complete dissimilarity to exact similarity, respectively. Conversely, the Hausdorff distance metric measures the maximum separation between two sets, offering a different perspective on segmentation accuracy, albeit being sensitive to outliers. While prioritizing the improvement of the DICE score for overall similarity, the inclusion of the Hausdorff distance metric serves to identify outliers in the segmentation output.

7 References

[1] Bangalore Yogananda, C. G., Shah, B. R., Vejdani-Jahromi, M., Nalawade, S. S., Murugesan, G. K., Yu, F. F., Pinho, M. C., Wagner, B. C., Emblem, K. E., Bjørnerud, A., Fei, B., Madhuranthakam, A. J., Maldjian, J. A.(2020, June). *A fully automated deep learning network for Brain Tumor Segmentation.* Tomography (Ann Arbor, Mich.). `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7289260/`

[2] faizan1234567. (2024). FAIZAN1234567/Brats23-tumors-segmentation: Brain tumors segmentation on 3D MRI images. GitHub. `https://github.com/faizan1234567/BraTS23-Tumors-Segmentation`

[3] Papers with Code. *3D MRI brain tumor segmentation using auto-encoder regularization*. Papers With Code. (2018). `https://paperswithcode.com/paper/3d-mri-brain-tumor-segmentation-using/review/`

[4] Papers with Code. *Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks*. Papers With Code. (n.d.). https://paperswithcode.com/paper/automatic-brain-tumor-segmentation-using-1

[5] Papers with Code. *A Two-Stage Cascade Model with Variational Autoencoders and Attention Gates for MRI Brain Tumor Segmentation*. Papers With Code. (2020). https://paperswithcode.com/paper/a-two-stage-cascade-model-with-variational

[6] Papers with Code. *Brain Tumor Segmentation with Deep Neural Networks*. Papers With Code. (n.d.). https://paperswithcode.com/paper/brain-tumor-segmentation-with-deep-neural

[7] Papers with Code. *nnU-Net for Brain Tumor Segmentation*. Papers With Code. (2020). https://paperswithcode.com/paper/nnu-net-for-brain-tumor-segmentation

[8] Shelhamer, E., Long, J., and Darrell, T. (2017). Fully Convolutional Networks for Semantic Segmentation. IEEE transactions on pattern analysis and machine intelligence, 39(4), 640–651. https://doi.org/10.1109/TPAMI.2016.2572683