

Weekly Project Report – 1



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Automated Multi-Parametric MRI Segmentation of Post-Treatment Glioma Sub-Regions Using Classical Machine Learning and Contour-Based Methods

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Abstract—Gliomas are brain tumors which can be aggressive and highly recurrent in spite of surgery and treatment. MRI scans are conducted after treatment to control tumor recurrence and determine the response to treatment. These scans are however difficult to interpret since they might be confused with surgical cavities, radiation effects, necrosis and edema.

The goal of the project is to research and create an automated system of segmenting post-treatment glioma sub-regions with multi-parametric MRI data. Week-1 was dedicated to the mastery of the clinical background, the study of the data structure, and the analysis of the literature on the topic and significant issues regarding this problem.

I. INTRODUCTION

Gliomas are formed on the basis of glial cells and are one of the worse forms of brain tumors. Treatment is typically done with surgery and then chemotherapy and radiotherapy. Complete treatment still does not prevent recurrence. Thus, MRI follow-up is regularly used to monitor disease progress. Clinicians can use these MRI scans to:

- Identify the occurrence of tumor reappearance,
- Record tumor growth progressively,
- Assess the success of therapy,
- Test further treatment as necessary.

Nonetheless, post-treatment MRI scans are much more important and more complicated than pre-treatment scans. Surgical removal will alter the normal structure of the brain, radiation affects both tumor and normal tissues, and necrosis may resemble active tumor tissue. This complexity makes it hard to perform segmentation manually and encourages the requirement of computerized methods.

II. UNDERSTANDING POST-TREATMENT CHALLENGES

Post-treatment glioma segmentation is more difficult compared to pre-treatment cases. After surgery or radiation therapy, the structure of the brain changes, which makes tumor identification harder.

- Surgical removal leaves cavities that alter the normal brain structure.
- Radiation can cause tissue damage that looks similar to tumor regions.
- Edema and fluid accumulation affect the intensity patterns in MRI scans.
- The boundaries between healthy and affected tissues become less clear.

During our preliminary analysis of the dataset, we observed that tumor appearance varies significantly across patients. In some cases, the tumor regions are clearly visible, while in others the boundaries are irregular and difficult to distinguish. This variability makes segmentation more challenging and requires careful analysis.

III. DATASET DESCRIPTION

The information that will be utilized in the project is founded on the BraTS benchmark project. The BRATS study [1] provided standardized tumor tags and measurements that are commonly used in research on brain tumor segmentation.

Any patient case is comprised of four MRI modalities:

- **T1-weighted (T1):** Anatomical structure.
- **T1 with contrast (T1Gd):** Highlights the tumor.
- **T2-weighted (T2):** Sensitive to fluid and structures.
- **FLAIR:** Focuses on edema and pathology.

Both of the above scans are 3D volumetric images in NIfTI format. The above dataset also includes ground truth masks of the sub-regions of the tumors, marked by experts.

During Week-1, we were ready to prepare some sample cases and visualize the different modalities and different slices. This reminded us of the variation in image of the tumor regions in both kinds of scan.

A. 2D Slice Visualization

Every MRI scan is made up of numerous stacked axial slice to create a 3-D brain volume. To obtain preliminary results on the dataset, we plotted the representative slices of the four MRI modalities given in the BraTS dataset: T1, T1Gd (T1CE), T2, and FLAIR, and the corresponding segmentation mask.

The four modalities obtain various tissue characteristics:

- **T1:** A clear anatomy of the brain is provided and assists in identifying normal tissue margins.
- **T1Gd (T1CE):** Obtained following contrast injection; shows active tumor enhancement.
- **T2:** The use of T2 makes fluid areas bright and assists in tumor spread visualization.
- **FLAIR:** It will cause the normal fluid signals to be suppressed and increase the edema (swelling around the tumor).

A comparison of these modalities with each other would reveal the way the tumor and surrounding tissues can change in their appearance as imaging methods are used. This multi-modal representation gives complementary information and this information is helpful to give accurate tumor segmentation.

The segmentation mask provides marked tumor sub-regions that are to help as ground truth in training and evaluating machine learning models.

Figure 1 shows representative axial slices from all four MRI modalities along with the corresponding segmentation mask.

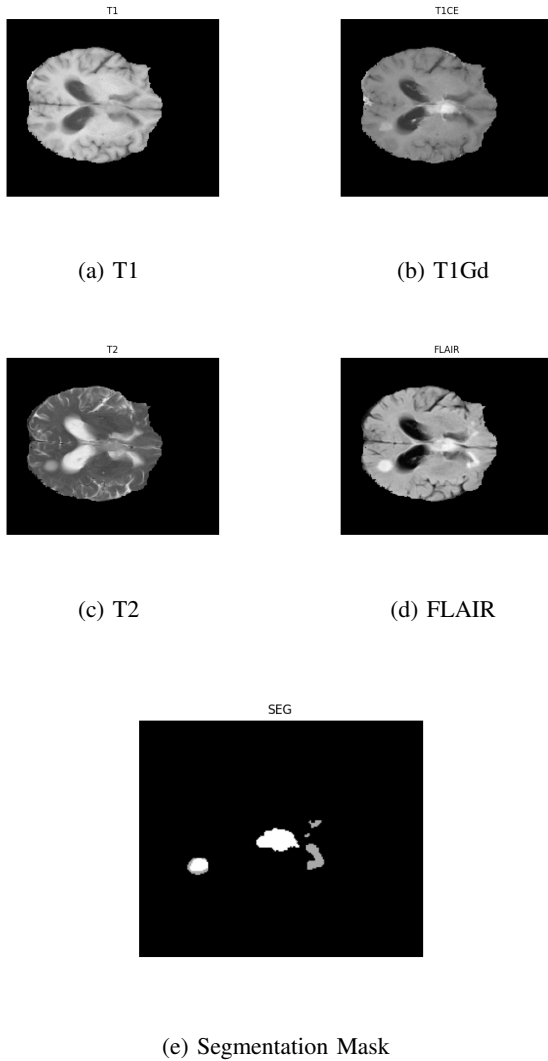


Fig. 1: Representative axial slices from the four MRI modalities (top) and the corresponding tumor segmentation mask (bottom).

IV. EVALUATION METRICS

In segmentation of medical images, the overlap-based metrics are usually used to measure performance. Based on our literature review, we found such popular metrics as:

- Dice Similarity Coefficient (measures the overlap of the prediction and ground truth),
- Hausdorff Distance (measures the accuracy of the boundary),
- Sensitivity and Specificity.

Knowledge of these measures early on helps to design experiments that are benchmark aligned.

V. INITIAL LITERATURE STUDY

We have performed a preliminary literature review to know the way this issue has been tackled in the past.

The BRATS benchmark paper [1] points out that even specialist radiologists might not be able to agree on tumor borders, which suggests that the process of segmentation is not an easy task.

We also reviewed studies that apply classical machine learning methods. These approaches typically involve inference of the pertinent features of MRI scans and supervised classifier segmentation. From these studies, we understood the importance of feature representation, handling class imbalance, and careful evaluation.

This literature review helped us gain insight into the strengths and limitations of previous work.

VI. CHALLENGES IDENTIFIED

Based on dataset exploration and literature review, we identified several challenges:

- Great heterogeneity of tumors appearance in patients,
- Intensity overlap between tumor and non-tumor tissues,
- Inequality in distribution of voxels,
- Large size and computational complexity of 3D MRI volumes.

Addressing these challenges will be important in designing a robust segmentation approach.

VII. WORK COMPLETED IN WEEK-1

In the course of Week-1, we worked on the problem consideration and familiarization with the dataset. The tasks that were accomplished include:

- Learned about the fundamentals of post-treatment glioma and associated clinical history.
- Obtained and prepared the BraTS dataset.
- To learn about various modalities, visualized MRI volumes.
- Handling tumor segmentation labelling and sub-regions.
- Began reading pertinent review papers in brain tumor segmentation.

All in all, the week was spent on developing the clear vision of the dataset and the issue prior to beginning to implement the models.

VIII. PLAN FOR WEEK-2

During Week-2, we will further refreeze our grasp of current research and will start putting it into practice. The tasks to be done are as follows:

- Entire perusing of the chosen review articles.
- Learn the progress that has been made in tumor segmentation in the past.

- Start working on the introduction of simple preprocessing actions.
- Discover additional enhancements with the help of literature.

Week-2 is aimed at taking a slow transition between theoretical knowledge and practical experimentation.

REFERENCES

- [1] 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, Oct. 2015.