Tumor Grade Classification and Segmentation in Lower-Grade Gliomas Using Deep Learning

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Abstract

Lower-Grade Gliomas (LGG) are a subset of brain tumors that pose unique challenges due to their heterogeneous nature and varying levels of aggressiveness. Accurate segmentation of tumor regions in MRI images and precise classification of tumor grades are crucial for effective treatment planning and prognosis. This project proposes a multi-task deep learning framework leveraging the LGG Segmentation Dataset, which includes multi-sequence MRIs and clinical data for 110 patients. The proposed framework consists of a U-Net-based segmentation model and a ResNet-based classifier to identify tumor regions and predict tumor grades. Our model aims to automate the process of tumor detection and grading, enhancing the efficiency and accuracy of clinical decision-making.

1. Introduction

Lower-Grade Gliomas (LGG) are a class of primary brain tumors that typically manifest with varied degrees of malignancy, necessitating precise characterization to guide treatment. Current clinical workflows rely heavily on manual interpretation of MRI scans, which is time-consuming and susceptible to inter-observer variability [3]. Deep learning-based approaches can significantly automate and standardize these processes, improving outcomes for patients [2]. This project aims to address the problem of automatic tumor segmentation and grade classification using multi-sequence MRI data and patient clinical information. Our key contributions include:

- Development of a multi-task learning model to simultaneously perform tumor segmentation and classification.
- Integration of MRI imaging features with clinical metadata to enhance classification performance.
- Comprehensive evaluation using relevant metrics such as Dice Score and F1-Score.

2. Dataset Description

The dataset used for this project is the **LGG Segmentation Dataset** from Kaggle, which contains brain MRI images along with segmentation masks and clinical data for 110 patients. Each patient's data is organized into a separate folder with MRI slices in '.tif' format and their corresponding segmentation masks.

- **Source:** LGG Segmentation Dataset on Kaggle [1].
- **Number of Patients:** 110.
- **Data Format:** Each patient folder contains multiple MRI slices and corresponding segmentation masks in '.tif' format.
- **Image Structure:** Each MRI image is a 3-channel '.tif' image representing pre-contrast, FLAIR, and post-contrast sequences.
- **Segmentation Masks:** Binary masks highlighting tumor regions.
- **Clinical Data:** Additional patient metadata such as tumor grade, age, gender, and genomic cluster identifiers.

Figure 1 illustrates sample MRI images and corresponding segmentation masks from the dataset.

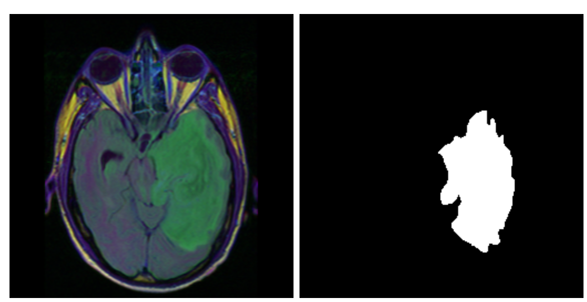

Figure 1. Sample MRI Image and Corresponding Segmentation Mask from the LGG Dataset [1].

Table 1 provides the clinical metadata for two sample patients, including tumor grade, histological type, and survival status.

Table 1. Clinical Metadata for Sample Patients

Patient	Grade	Histology	Gender	Age	Survival
TCGA_CS_4942	2	1	Male	44	Deceased
TCGA_CS_5393	2	1	Female	39	Alive

3. Proposed Method

Our proposed methodology consists of two interconnected models:

- **Segmentation Model**: We employ a U-Net architecture [4] for precise segmentation of tumor regions. The model will be configured with a depth of 5 layers, using ReLU activation functions and a Dice Loss [2] to optimize the overlap between predicted and ground-truth masks.
- **Classification Model**: A ResNet50-based classifier will be utilized to predict the tumor grade (Grade 1 or Grade 2) based on the segmented regions. The model will be pre-trained on ImageNet and fine-tuned using the segmented tumor regions along with patient clinical data (e.g., age, gender) as additional inputs.

The segmentation model will first generate binary masks of the tumor regions, which will then be used as input for the classification model. This approach allows for both pixel-level and image-level understanding of the tumor characteristics.

4. Conclusion

In this project, we proposed a multi-task deep learning framework for automatic tumor segmentation and grade classification in Lower-Grade Gliomas using MRI images. The combination of a U-Net-based segmentation model and a ResNet-based classifier enables both precise localization of tumor regions and accurate grade prediction. By leveraging the LGG Segmentation Dataset, which includes multi-sequence MRI data and clinical metadata, our model aims to enhance the automation of tumor detection and improve the grading process, providing a comprehensive tool for clinical decision-making. However, since the dataset primarily contains Grade 1 and Grade 2 tumors, the grade classification task may have limited clinical relevance due to the lack of higher-grade examples. Thus, the primary focus of this work will be on improving the segmentation accuracy. In future work, we plan to explore more advanced architectures and integrate additional clinical data, such as genomic information, to further refine our model's predictive capabilities.

References

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