Project Progress Report: Tumor Grade Classification and Segmentation in Lower-Grade Gliomas Using Deep Learning

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Abstract

This report describes the progress made on the project involving the development of a multi-task deep learning framework for Lower-Grade Glioma (LGG) segmentation and tumor grade classification using MRI images and clinical data. We implemented a U-Net for segmentation and a ResNet50-based classifier for grade prediction. The training process is ongoing, and optimization for performance and training time will be the next step.

1. Introduction

Our project focuses on automating the segmentation and classification of brain tumors (Lower-Grade Gliomas) using MRI images. The framework integrates image features with clinical metadata, such as tumor grade and age, to predict tumor grades and localize tumor regions, which is critical for accurate diagnosis and treatment planning.

2. Work Done to Date

We began the project with an exploratory data analysis (EDA) of the LGG dataset, which included a detailed examination of clinical metadata and MRI image characteristics. The analysis included checking for missing data, understanding the distribution of tumor grades, and reviewing sample MRI images and segmentation masks to assess data quality and consistency.

After the EDA, we proceeded with the preprocessing stage. The MRI images and corresponding segmentation masks were resized to a uniform target size and normalized to prepare them for model training. We also integrated clinical metadata with the preprocessed images, ensuring that both imaging and clinical data were available for the machine learning models.

In terms of model implementation, we developed a U-Net architecture for the segmentation task. The U-Net model was configured with five convolutional layers, and we employed Dice Loss to optimize the overlap between predicted tumor masks and ground-truth masks [2]. Additionally, we implemented a ResNet50-based classifier for the tumor grade prediction task. The ResNet50 classifier was pre-trained on ImageNet and fine-tuned using segmented tumor regions along with clinical metadata [1].

Currently, we are in the process of training the models. However, the training process has been slower than expected, with the initial training run taking approximately 140 minutes and still ongoing. We are exploring optimization techniques to improve training efficiency in the next steps.

3. Next Steps

Moving forward, we will implement data augmentation techniques to address the issue of limited data size. Techniques such as random rotation, flipping, and contrast adjustments will be applied to improve model generalization [2]. We will also focus on optimizing the models by experimenting with different architectures, learning rates, and batch sizes to reduce training time and enhance performance.

Once the training is completed, we will evaluate the models using relevant metrics such as the Dice Score for segmentation and classification accuracy for tumor grade prediction. Additionally, we will experiment with dropout layers to prevent overfitting and techniques to handle potential class imbalances in the dataset.

4. Individual Contributions

Alishbah Fahad has been responsible for the initial exploration of the dataset, implementing the preprocessing steps, and developing the U-Net segmentation model. Sai Ganesh Reddy Katasani worked on the development of the ResNet50 classifier, integrating the clinical metadata with the MRI images, and contributing to the training and evaluation of the models.

5. Conclusion

Significant progress has been made in both the exploratory and implementation phases of the project. The models for segmentation and classification have been developed and are currently being trained. Further work will focus on optimizing the training process and improving the performance of the models through data augmentation and hyperparameter tuning. We anticipate completing the analysis and refinement in the coming weeks, based on the results of the current training run.

References

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[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, pages 234–241. Springer, 2015.