BRAIN TUMOUR SEGMENTATION FOR SUB-SAHARAN AFRICAN POPULATION USING 3D UNET

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Introduction

Glioma is a deadly brain tumor with a survival rate of less than 5%[1], particularly affecting Sub-Saharan Africa (SSA) where screening and early diagnosis challenges persist[2]. Medical image analysis with accurate segmentation is crucial for diagnosis, disease monitoring, and treatment response. The BraTS challenge has spurred advancements in brain tumor segmentation[3]. To address SSA's unique needs, BraTS-Africa was introduced[4] with a dataset reflecting the region's realities.

However, data imbalance and low sample size in BraTS-Africa pose challenges. The tumor sub-regions - Necrotic Core (NC), Enhancing Tumor (ET), and peritumoral oedema (OD) - show complex interactions and are hard to segment. Late presentations in SSA are linked to limited MRI access and image quality issues[4]. The dataset has only 60 training and 15 validation sets, unlike the large BraTS dataset[5].

To overcome these challenges, we propose a hybrid network approach. We integrate wavelet noise mapping to the UNet encoder path[6] and implement attention modules on skip connections[7]. This hybrid model aims to improve segmentation accuracy, especially in the low-resource SSA context.

Data Collection

The BraTS-Africa dataset[5] comprises 95 cases, divided into training/validation/testing sets with a split of 60/15/20 cases, respectively. Each case includes T1, T2, T1CE, and FLAIR scans, along with corresponding sub-region labels. All scans and segmentations are stored as NiFTI files. Like the typical BraTS dataset, it contains clinically acquired multiparametric scans (T1, T2, T1CE, and FLAIR) and sub-region labels - Peritumoral Oedema (OD), Enhancing Tumour (ED), and Necrotic Core (NC).

The BraTS-Africa data was processed similarly to the BraTS continuous evaluation dataset. All volumes were co-registered to the SRI Atlas[8], corrected for bias using N4 Bias correction, skull stripped, and resampled to an isotropic resolution of 1mm³.

Data Processing

Each scan in the dataset has dimensions of 240 x 240 x 155. Preprocessing involved cropping out the foreground and normalizing the intensities of the non-zero region in the MRI scans.

Data augmentation techniques, such as resampling and cropping, were applied to both the images and corresponding labels to increase the dataset size and reduce overfitting.

Methodology

Model Architecture:
The Optimized UNet[9] served as our baseline network, selected for its strong performance in glioma sub-region segmentation. The model was augmented by introducing a wavelet function at the encoding path entrance and integrating attention mechanisms at each UNet layer.

Loss Function:
A combination of binary cross-entropy and Dice loss functions was employed to enhance the segmentation accuracy of individual sub-regions. These selections were based on their established efficacy in brain tumor segmentation[9].

Training:
Each model experiment entailed 30 epochs of training, using a learning rate of 0.0003, a depth of 6, and a minimum feature map size of 2. Validation utilized the provided dataset, and checkpoints were saved per epoch, with special attention to identifying the best validation epoch.

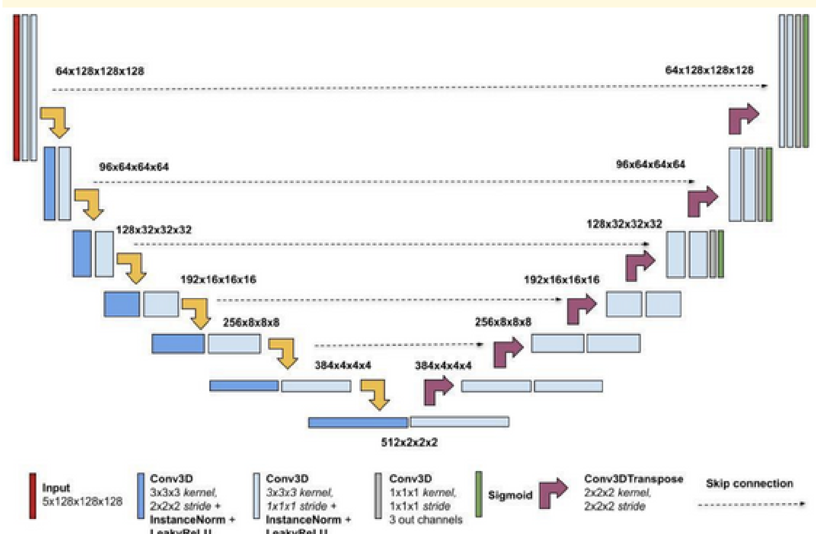

Fig. 1. UNet Architecture hybridised with wavelet noise mapping and attention mechanism.

Results

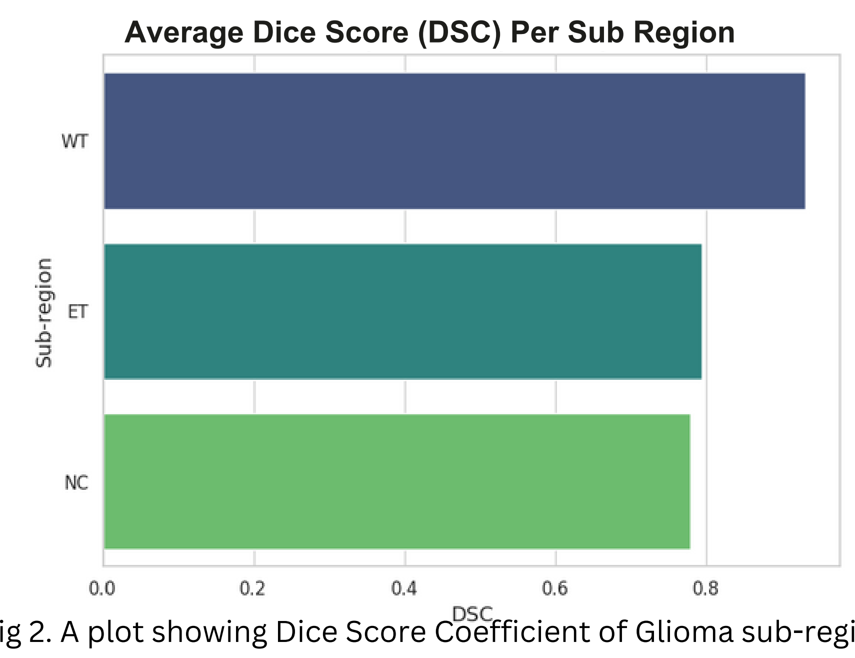

Fig 2. A plot showing Dice Score Coefficient of Glioma sub-region

SUB-REGION	WT	ET	NC	AVG
DSC	0.9312	0.796	0.779	0.836

Table 1. Dice Score Coefficient of Glioma sub-region

Challenges

- Limited data availability and diversity, resulting in a small and imbalanced dataset.
- Variability in image quality and noise in the BraTS-Africa dataset, affecting model generalization.
- Challenges in accurately labeling tumor sub-regions due to the complexity and variability of glioma tumors.
- Insufficient computational resources for extensive model training and hyperparameter tuning.
- Variability in MRI machine settings and protocols across different medical centers contributing to inconsistent data quality.

Next Steps

- Improve segmentation accuracy for low-labelled sub-regions.
- Explore wavelet noise mapping and attention mechanisms for better UNet performance.
- Gather more diverse data from SSA for model generalizability.
- Optimize the model for clinical use in SSA's brain tumor diagnosis and treatment.
- Deploy the model and build interface for usage.

Discussion

The findings demonstrate that baseline UNet can segment the sub-region of Glioma tumours obtained from the SSA region despite the peculiarity of the BraTS-Africa dataset in terms of image quality, noise, large tumour volume and unequal sub-region labelling.
However, the results obtained in this study suggests that a machine learning model can be developed to address the diagnostic needs of this region using the BraTS-Africa dataset. However, there is need to significantly improve the segmentation accuracy of the model, especially on sub-regions with lower labelling coverage.

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