Brain Tumour Segmentation for Sub-Saharan African Population Using 3D UNet

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Abstract. Patients diagnosed with Glioma generally have a survival rate of less than two years. The severity of the disease is even worse in low-resource settings such as Sub-Saharan Africa (SSA). Glioma in SSA is characterized with advanced stage presentation and large tumour volume. The Brain tumour segmentation (BraTS) Challenge featured dataset from SSA for the first time ever since running for more than a decade. The peculiarity of the location where these data were obtained finds its way into the dataset. Issues such as image quality, noise, unusually large tumours and low number of samples in the dataset, this makes the dataset different from what is obtainable in developed regions. Dataset imbalance also exists among the labelling of the sub-regions of the brain tumour with Peritumoral Oedema (OD) having larger labelling compared to Enhancing Tumour (ED) and lastly Necrotic Core (NC). This study aims to address the labelling imbalance, low number of samples and the unusual characteristic features of BraTS-Africa da taset. Here, we implemented UNet to develop African brain tumour segmentation model. An average Dice Score Coefficient (DSC) of 0.8355. This study suggests the effectiveness of attention module and wavelets in improving the performance of UNet. Despite the peculiarity of Dataset obtained from SSA, A deep learning model can be developed to address the diagnostic need of the region.

Keywords: Attention module, Wavelets, UNet, Segmentation, BraTS-Africa, Glioma, MRI

1 Introduction

Glioma is a severe type of brain tumour. With a survival rate of less than 5%, most patients die after two years[1]. The disease is more deadly in Sub-Saharan Africa (SSA) where several issues affect screening and early diagnosis[2], [3]. Accurate image segmentation is important in medical image analysis to enable clinicians to obtain meaningful information from the image, this is crucial for diagnosis, monitoring disease progression and response to treatment. The Brain Tumour Segmentation (BraTS)[4]–[7] challenge has been running for more than a decade to encourage the development of state-of-the-art network architectures for the segmentation of the sub-region of the brain. This year, it introduced for the first time ever, the BraTS-Africa[8] sub-challenge to obtain brain tumour segmentation models that will effectively segment the sub-regions of Glioma in SSA, to enable accurate and rapid diagnosis of the disease in the region.

A balanced dataset has been evidenced to always give best model performance. Most efforts in Machine learning are often spent in data cleaning and preparation. However, the true nature of some dataset just doesn't allow it to be balanced. The Necrotic Core (NC) of an adult diffuse glioma always contains dead cells and it the origin of the neoplasm. It is always surrounded by the Enhancing Tumour (ET) which is a mixture of dead and living cells with a warped level of vasculature. The ET occupies a larger volume enclosing the NC. The peritumoral oedema (OD) is the swelling of observed in healthy tissue surrounding the ET which is nested with the NC thereby occupying the largest volume. This labelling is also observed on each slice of the scan with OD always encompassing ET and NC.

The peculiarity of BraTS-Africa dataset is a true reflection of the settings where the data was obtained. Late presentation of cases are often due to lack of access to MRI[9], [10], the barrier is often economic, personnel or infrastructure. Image quality is also an issue as most centres do not engage in the quality assurance of their MRI systems. Access to contrast agents, improperly setup Picture Archiving and Communication Systems (PACs) to mention a few. These are part of the reasons that contributed to the low number of cases from this region. The BraTS-Africa dataset consist of 60 Training sets and 15 validations set. This is a sharp contrast to the BraTS continuous evaluation dataset that has 1251 training sets and 219 validation sets.

Since the introduction of UNet[11] for biomedical image segmentation, it has gained prominence as the leading network architecture. Several variants have been made over the years to improve its performance such as VNet[12], nn-UNet[13], SwinUneTr[14] and Optimized UNet[15]. This number will keep increasing as AI researchers keep looking for the optimum network architecture for brain tumour segmentation for application in the clinics.

Attention module helps to focus the attention of the network on important and selective features of the image during training especially hard to segment regions. This has been shown to improve the performance of UNet[16]–[18] especially when the number of dataset is low or imbalanced while reducing computational resources utilization.

Wavelet, originally used for signal processing, image reconstruction and noise reduction[19] have also been shown enhance the performance of deep neural networks when fused with to the encoder path[20].

In this study, we introduce a wavelet noise mapping to the encoder path of UNet and implement attention module on each skip connection to produce a hybrid network that caters for the low number of samples in the dataset, dataset labelling imbalance among the tumour sub-regions and image quality issues characterising the BraTS-Africa dataset.

2 Method

2.1 Data

The BraTS-Africa dataset[8] has a total of 95 cases, split into 60/15/20 for training/validation/testing sets respectively. Each case consists of T1, T2, T1CE and FLAIR scans and the corresponding sub-region labelling. All scans and the segmentations are NiFTI files.

Typically, BraTS dataset features clinically acquired multiparametric scans (T1, T2, T1CE and FLAIR) and the sub-region labelling - Peritumoral Oedema (OD), Enhancing Tumour (ED) and Necrotic Core (NC). BraTS-Africa data is no exception, it was processed similarly to the BraTS continuous evaluation dataset. All volumes were co-registered to the SRI Atlas[21], corrected for bias using N4 Bias correction, skull stripped and resampled to the isotropic resolution of $1mm^3$.

2.2 Data Preprocessing and Augmentations

Each scan has a dimension of 240 x 240 x 155. All scans were processed by cropping out the foreground and normalizing intensities of only the non-zero region on the MRI. To increase reduce overfitting by increasing the number of datasets, data augmentation techniques such as resampling and cropping were implemented to both images and label. This was executed with prepare_dataset.py and preprocess.py.

2.3 Model architecture

The Optimized UNet[15] served as our baseline network, this is due to its high accuracy in segmenting the subregions of glioma. A new hybrid model was created with the addition of a wavelet function at the entrance of the encoding path and the insertion of attention mechanism at each layer of the UNet.

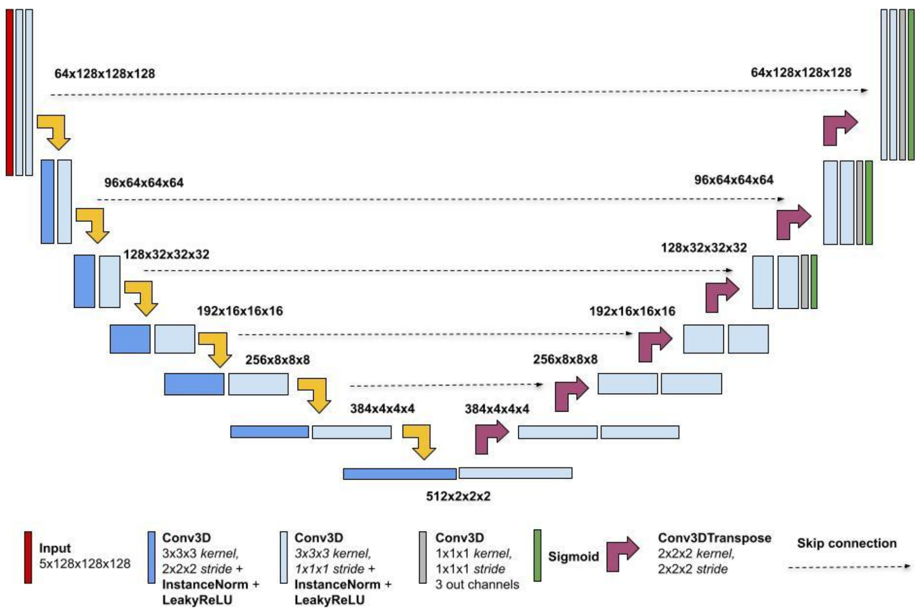

Fig. 1. UNet Architecture hybridised with wavelet noise mapping and attention mechanism.

2.4 Loss function

Each of the sub-regions was uniquely optimised with binary cross-entropy with the Dice loss. This was based on its evidenced performance for brain tumour segmentation[15].

2.5 Inference

The model inference was established to performance of the model on test dataset. This sub-section will be better detailed when test dataset becomes available.

3 Results

3.1 Implementation

All codes for this study was written in python utilizing the PyTorch library and extends the optimized UNet. The code will be made publicly available on Github at the conclustion of this study. All training and validation were conducted on the Digital Research Alliance of Canada High-Performance Computing (HPC) Infrastructure (https://alliancecan.ca/en) with access to V100 GPU. The proposed solution will be containerised as a docker image for submission to MLCube.

3.2 Training Schedule

Each experiment was trained for 30 epochs with a learning rate of 0.0003 at a depth of 6 with a minimum feature map of 2. Each experiment was also validated using the provided validation dataset. A checkpoint was saved for each epoch while noting the best epoch for validation.

3.3 Experiments

We experimented with the training the model with UNet as the baseline architecture on BraTS-Africa data. The result is as shown in table 1 below.

Table 1. Dice Score Coefficient of Glioma sub-region

Sub-region	DSC
WT	0.9317
ET	0.7956
NC	0.7791
AVG	0.8355

The network achieved DSC values of 0.9317, 0.7956 and 0.7791 for WT, ET, and NC sub-regions respectively. These values compare favourably to other state-of-the-art models that have been developed on the BraTS dataset previously.

4 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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