Self Supervised learning on Brain Tumor Segmentation (BraTS) dataset

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1 Abstract

This report presents a self-supervised learning framework for medical image analysis, focusing on brain tumor segmentation in MRI scans. The approach leverages a convolutional autoencoder to extract meaningful features from unlabelled medical images and utilizes these features for the downstream task of tumor segmentation.

2 Introduction

Medical image analysis plays a crucial role in diagnosing diseases and guiding medical interventions. However, labelled medical data is often scarce and expensive to obtain due to the need for expert annotation. This assignment aims to develop a self-supervised learning framework for medical image analysis, leveraging unlabelled data to learn meaningful representations for downstream tasks such as tumor segmentation.

3 Methodology

The methodology involves using a convolutional autoencoder to learn features from unlabelled MRI scans. The learned features are then used to perform brain tumor segmentation.

3.1 Data Preparation

The data can be accessed from here. Each scan includes FLAIR, T1, T1CE, and T2 modalities, along with segmentation masks. The data is preprocessed to normalize the images and resize them to a common dimension for input into the model.

3.2 Autoencoder Architecture

The autoencoder architecture consists of an encoder and a decoder. The encoder compresses the input image into a latent representation, while the decoder reconstructs the segmentation mask from this latent representation.

The encoder comprises four convolutional layers, each followed by a rectified linear unit (ReLU) activation function. The number of neurons in these layers ranges from 32 to 256. Each convolutional layer utilizes a (3,3) kernel for convolutional operations. Additionally, max-pooling layers with a kernel size of (2,2) are employed for downsampling and feature extraction.

Similarly, the decoder consists of four convolutional layers with the same kernel size as the encoder. These layers use the ReLU activation function as well. The decoder also employs up-sampling layers to reconstruct the segmentation mask to the original image size.

Overall, the autoencoder architecture aims to effectively compress the input image into a latent space and reconstruct the segmentation mask with high fidelity, enabling meaningful feature extraction for subsequent tasks.

The autoencoder architecture utilizes the softmax activation function for the output layer. This activation function is applied to the final convolutional layer in the decoder. By using softmax activation, the model ensures that the output values are transformed into probabilities, which is crucial for multi-class segmentation tasks like the one discussed here.

3.3 Training Process

The autoencoder model is trained over multiple epochs using a custom data generator. The training process includes monitoring the training and validation accuracy and loss to prevent overfitting.

4 Results

4.1 Training and Validation Performance

The training and validation accuracy and loss are plotted to visualize the training process. The figures below illustrate the performance of the model over the training epochs.

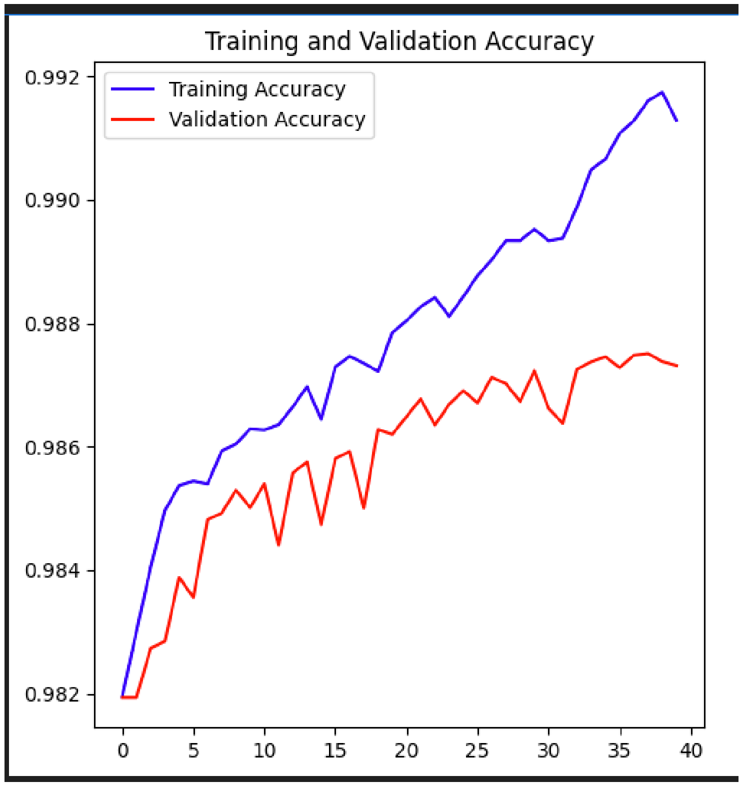

Figure 1: Training and validation accuracy over epochs.

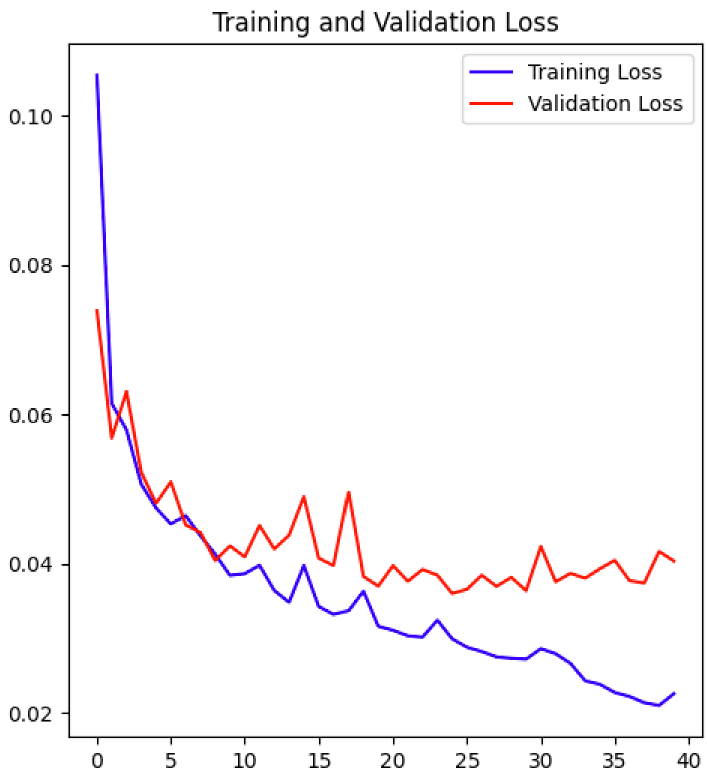

Figure 2: Training and validation loss over epochs.

5 Conclusion

This project successfully implemented a self-supervised learning framework for medical image analysis. The convolutional autoencoder model effectively learned features from unlabelled MRI scans and used these features to perform accurate brain tumor segmentation. Future work may explore extending this approach to other medical imaging modalities and further improving the model's performance.

6 References

- BraTS dataset: `https://www.kaggle.com/code/rastislav/3d-mri-brain-tumor-segmentation-u-n` `input`
- Relevant literature on self-supervised learning and autoencoders