

Configuration Manual for Advancing Biomedical Image Segmentation of Lower-Grade Gliomas using Transfer Learning

MSc Research Project Msc in Data analytics

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MSc Project Submission Sheet

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Configuration Manual for Advancing Biomedical Image Segmentation of Lower-Grade Gliomas using Transfer Learning

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1. Introduction

This configuration manual provides detailed instructions for setting up and running the model used in the research titled "Advancing Biomedical Image Segmentation of Lower-Grade Gliomas using Transfer Learning" using the Swin Transformer model for tumor segmentation in MRI images of lower-grade gliomas (LGGs).

The manual includes software requirements, hardware configurations, and step-by-step guidance on how to prepare the environment, dataset, and model for training, validation, and testing.

2. Prerequisites

Before you start, make sure you have the following:

2.1. Hardware Requirements

- GPU: A machine with at least one NVIDIA GPU (e.g., GTX 1080 or better) is highly recommended for training deep learning models.
- RAM: Minimum 16 GB RAM.
- Storage: SSD with at least 50 GB of free space for storing datasets and models.

2.2. Software Requirements

- Operating System: Linux (Ubuntu 18.04 or later), Windows (with WSL2), or macOS.
- Python: Version 3.8 or later.
- CUDA and cuDNN: For GPU acceleration (Optional, but recommended for faster training).
- Libraries and Frameworks:
 - TensorFlow or PyTorch (depending on which framework is used for implementation)
 - transformers library (from Hugging Face, for using transformer models)
 - scikit-learn
 - matplotlib, seaborn (for plotting and visualization)
 - opency-python, Pillow (for image processing)
 - SimpleITK, nibabel (for handling medical imaging formats like MRI scans)

3. Dataset Configuration

3.1. Dataset Overview

The dataset used for training and evaluation in this project is the LGG-MRI dataset, which consists of MRI scans of patients with lower-grade gliomas along with their corresponding tumor masks.

- Format: TIFF images and binary segmentation masks.
- Size: 256x256 pixel images.

3.2. Dataset Setup

Download the Dataset:

• The dataset can be downloaded from Kaggle or other public repositories.

• Make sure the images and masks are organized in directories as follows:

```
(7858,
 ['dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_8 mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_9_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_2_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_3_mask.tif'
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_20_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_9.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_15_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_14_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle 3m/TCGA CS 6667 20011105/TCGA CS 6667 20011105 8.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_16.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_18_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_19_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_17.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_15.tif'
  dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_14.tif'
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_12_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_13_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_10.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_11.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_13.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_5_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_4_mask.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_12.tif',
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_16_mask.tif'
  'dataset/lgg-mri-segmentation/kaggle_3m/TCGA_CS_6667_20011105/TCGA_CS_6667_20011105_17_mask.tif'])
```

• Resize images to a consistent size (e.g., 256x256 pixels).

```
# Processes the image
def decode_and_resize_image(img_path):
    # Reading '.tiff' format image
    img = tf.io.read_file(img_path)
    with tf.io.gfile.GFile(img_path, 'rb') as f:
        img = Image.open(f)
        img = np.array(img)
    img = tf.convert_to_tensor(img, dtype=tf.float32)
    img = tf.image.resize(img, IMAGE_SIZE, preserve_aspect_ratio=True)

# Normalizing the image to the range [0, 1]
    img = img / 255.0

return img
```

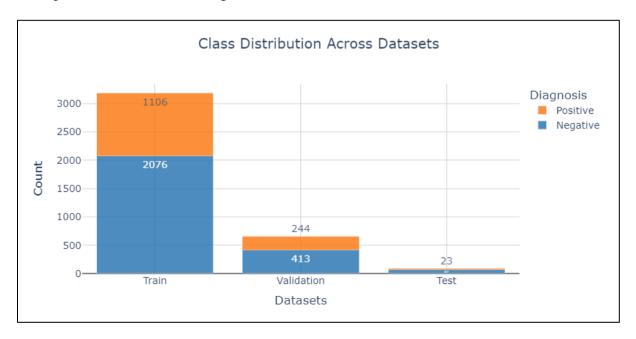
• Normalize pixel values (e.g., scale between 0 and 1).

```
# Processes the mask
def decode_and_resize_mask(mask_path):
    # Reading '.tiff' format masks
    mask = tf.io.read_file(mask_path)
    with tf.io.gfile.GFile(mask_path, 'rb') as f:
        mask = Image.open(f)
        mask = np.array(mask)
    mask = rf.convert_to_tensor(mask, dtype=tf.float32)
    mask = np.expand_dims(mask, axis=-1)
    mask = tf.image.resize(mask, IMAGE_SIZE, method='nearest', preserve_aspect_ratio=True)
    grayscale_mask = tf.reduce_mean(mask, axis=-1, keepdims=True)

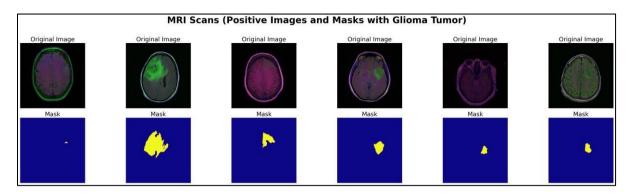
# Normalizing the mask to the range [0, 1]
    grayscale_mask = grayscale_mask / 255.0

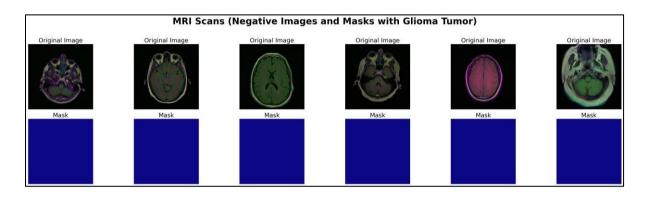
return grayscale_mask
```

• Split the dataset into training (70%), validation (15%), and test (15%) sets.



• Apply data augmentation (e.g., random rotations, zooming, flipping) to increase the diversity of the training set.





train_data.head()							
	ID	Image	Mask	Diagnosis			
812	TCGA_DU_5853_19950823_8	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	0			
1550	TCGA_DU_5871_19941206_15	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	0			
2228	TCGA_DU_8163_19961119_21	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	0			
1108	TCGA_DU_7304_19930325_11	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_DU	0			
3728	TCGA_HT_7881_19981015_52	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_HT	dataset/lgg-mri- segmentation/kaggle_3m/TCGA_HT	0			

4. Defining the Segmentation Model for Lower-Grade Glioma Segmentation through Transfer Learning

4.1. Load Pretrained Swin Transformer

The Swin Transformer model is available in the transformers library by Hugging Face. You can use a pretrained Swin Transformer model fine-tuned for image segmentation tasks.

4.2. Model Customization

To use the pretrained Swin Transformer for segmentation, modify the model architecture to include a final convolutional layer for pixel-wise classification:

4.3. Freezing Layers for Transfer Learning

Fine-tune only the later layers to adapt the model for medical imaging tasks:

```
# Building the Segmentation model
def build segmentation model(input shape=(256, 256, 3)):
    inputs = layers.Input(shape=input shape)
    # Use pre-trained Swin Transformer model layer (classification task)
   layer = SwinForImageClassification.from pretrained("microsoft/swin-base-patch4-window7-224")
   # Convolutional layers
   x = layers.Conv2D(32, (3, 3), padding='same', activation='relu')(inputs)
   x = layers.MaxPooling2D(pool size=(2, 2))(x)
   x = layers.Conv2D(64, (3, 3), padding='same', activation='relu')(x)
   x = layers.MaxPooling2D(pool_size=(2, 2))(x)
   x = layers.Conv2D(128, (3, 3), padding='same', activation='relu')(x)
   x = layers.MaxPooling2D(pool_size=(2, 2))(x)
   # Flatten the output for dense layers
   x = layers.Flatten()(x)
   x = layers.Dense(256, activation='relu')(x)
   x = layers.Dense(128, activation='relu')(x)
   # Output layer with a dense layer
   outputs = layers.Dense(input_shape[0] * input_shape[1], activation='sigmoid')(x)
   # Reshape output to match the input dimensions
   outputs = layers.Reshape((input_shape[0], input_shape[1], 1))(outputs)
   # Creating the model
   model = models.Model(inputs, outputs)
    return model
# Instantiate the model
model = build_segmentation_model()
# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# Summary of the model
model.summary()
```

5. Training Configuration for Segmentation Model

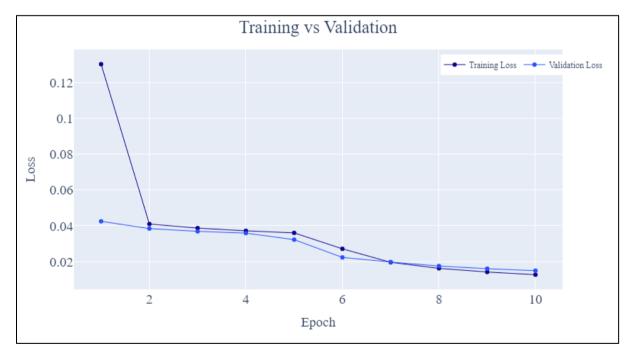
5.1. Hyperparameters

Adjust the following hyperparameters based on your system and dataset:

- Learning Rate: 0.001 (for Adam optimizer)
- Epochs: 10 (adjust based on convergence)
- Optimizer: Adam

• Loss Function: Binary Cross-Entropy for segmentation

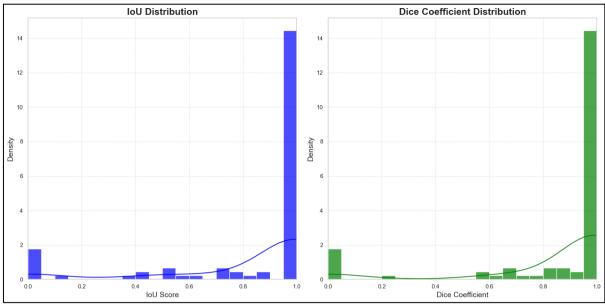
```
# Training the model
   history = model.fit(train_dataset, validation_data=validation_dataset,
      epochs=10)
Fnoch 1/10
71/71 -
                         - 81s 1s/step - accuracy: 0.9049 - loss: 0.2625 - val_accuracy: 0.9897 - val_loss: 0.0425
Epoch 2/10
                         - 99s 1s/step - accuracy: 0.9898 - loss: 0.0417 - val_accuracy: 0.9897 - val_loss: 0.0384
71/71 -
Epoch 3/10
                         - 98s 1s/step - accuracy: 0.9898 - loss: 0.0387 - val_accuracy: 0.9897 - val_loss: 0.0369
71/71 -
Epoch 4/10
71/71 -
                         - 114s 2s/step - accuracy: 0.9900 - loss: 0.0366 - val accuracy: 0.9897 - val loss: 0.0359
Epoch 5/10
71/71 -
                         - 101s 1s/step - accuracy: 0.9897 - loss: 0.0361 - val_accuracy: 0.9900 - val_loss: 0.0322
Epoch 6/10
71/71 -
                         - 116s 2s/step - accuracy: 0.9910 - loss: 0.0294 - val_accuracy: 0.9920 - val_loss: 0.0223
Epoch 7/10
                         - 108s 2s/step - accuracy: 0.9928 - loss: 0.0204 - val_accuracy: 0.9928 - val_loss: 0.0197
71/71 -
Epoch 8/10
                         - 110s 2s/step - accuracy: 0.9939 - loss: 0.0169 - val_accuracy: 0.9935 - val_loss: 0.0175
71/71 -
Epoch 9/10
71/71 -
                         - 107s 2s/step - accuracy: 0.9945 - loss: 0.0150 - val_accuracy: 0.9940 - val_loss: 0.0160
Epoch 10/10
                           121s 2s/step - accuracy: 0.9949 - loss: 0.0133 - val accuracy: 0.9943 - val loss: 0.0149
71/71 -
```



6. Evaluation Configuration

6.1. Segmentation Metrics

Evaluate the model using metrics like IoU, Dice Similarity Coefficient (DSC), and Confusion Matrix:





Classification	Report: precision	recall	f1-score	support
Negative Positive	1.00 0.78	1.00 0.72	1.00 0.75	5854882 43358
accuracy macro avg weighted avg	0.89 1.00	0.86 1.00	1.00 0.87 1.00	5898240 5898240 5898240

Conclusion

This manual provides the necessary steps to configure and run the segmentation model for lower-grade gliomas using a Swin Transformer-based architecture with transfer learning. By following this guide, users can replicate the results of this study or adapt the approach for their own medical imaging tasks.

References

Python: https://www.python.org

Dataset Source: https://www.kaggle.com/datasets/mateuszbuda/lgg-mri-segmentation