Brain Tumor Segmentation

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EDA (Exploratory Data Analysis):

Data Loading and Preparation:

- Loads MRI images (`temp_image_flair`, `temp_image_t1c`, `temp_image_t2`) and corresponding masks (`temp_mask`) from the BRATS dataset.

- Normalizes the images and converts masks to categorical form.

- Crops images and masks to a specific size (`temp_combined_images` and `temp_mask`).

Data Saving:

- If the mask contains at least 1% non-zero labels, it saves the image and its corresponding mask for further processing (`np.save`).

Architecture Design (3D U-Net):

- Model Definition:

  - Defines a 3D U-Net architecture for semantic segmentation.

  - The U-Net consists of a contracting path (encoder) followed by an expansive path (decoder).

  - Each level in the contracting path consists of 2 convolutional layers with dropout and max-pooling.

  - The expansive path uses transposed convolutions for upsampling and concatenates features from the contracting path.

  - Final layer uses a 1x1x1 convolution with softmax activation for multi-class segmentation.

Design (3D U-Net):

The Architecture Design for 3D U-Net involves defining a specialized model tailored for semantic segmentation tasks. This model is structured around the foundational concept of a U-Net, comprising both a contracting path (encoder) and an expansive path (decoder). Within the contracting path, each level integrates two convolutional layers, incorporating dropout and max-pooling operations to extract and consolidate features effectively. On the expansive path, transposed convolutions are employed for upsampling, allowing for the reconstruction of spatial information. Moreover, features extracted from the contracting path are concatenated to facilitate precise localization. The final layer of the model utilizes a 1x1x1 convolutional layer with softmax activation, enabling the segmentation of multiple classes. This architectural design enables the 3D U-Net to effectively capture intricate spatial dependencies and semantic information, making it well-suited for tasks such as medical image segmentation, particularly in scenarios like brain tumor identification.

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Key Components:

- EDA:

- Data loading, preprocessing, and saving.

- Ensuring data quality by checking mask usefulness.

Architecture:

- 3D U-Net model for semantic segmentation.

- Contracting (encoder) and expansive (decoder) paths.

- Transposed convolutions for upsampling.

Method

1**. Image and Mask Loading:**

- This step establishes functions such as `load_img` and `imageLoader` to facilitate the loading of batches of images and corresponding masks, a crucial initial phase for training the model effectively.

2. **Model Compilation and Training:**

- Here, the model compilation and training processes are delineated. The model is compiled separately from the `simple_unet_model` function, offering greater flexibility in the training workflow.

- A `simple_unet_model` is crafted, specifying input/output shapes and the number of classes, followed by the printing of a model summary for review.

3. **Model Testing and Visualization**:

   - This phase involves loading test images (`test_img`) alongside their ground truth masks (`test_mask`).

   - Subsequently, the trained model is employed to make predictions on these test images (`test_prediction`).

   - To verify the efficacy of the model, both the predictions and ground truth masks are visually inspected using matplotlib.

   - The visualization encompasses the original image, ground truth mask, and predicted mask, facilitating a comprehensive comparison.

   - Specifically, predictions for three distinct test images (designated as `img_num = 402, 34, 247`) are exhibited and archived for further scrutiny.

Overall, this methodological approach encapsulates the critical stages of model training and evaluation, from data loading to prediction visualization, underscoring a comprehensive and systematic methodology for the development and assessment of the segmentation model.