Liver Segmentation Project

This project aimed to develop a machine learning model to automatically segment liver tumours in 3D medical scans. Accurate tumour segmentation is crucial for treatment planning and disease monitoring in liver cancer patients.

What we did:

1. **Data Preparation:** We collected a dataset of medical images containing livers (CT scans or MRIs) and their corresponding masks, which highlight the liver region in each image.
2. **Model Training:** We trained different segmentation models, such as UnetPlusPlus, MAnet, and DeepLabV3Plus, using the prepared dataset. These models learn to identify patterns in the images that differentiate the liver from other tissues.
3. **Evaluation:** We evaluated the performance of the trained models on a separate unseen test dataset. This helps assess how well the models can generalize to new data.

Data Description

The dataset used for this project was acquired from Kaggle. The link is provided: (https://www.kaggle.com/datasets/prathamgrover/3d-liver-segmentation). It contains 3D medical scans of livers with tumours, in NIfTI format. Here's a breakdown of the data:

- **imagesTr**: This folder contains the training data set. Each file within `imagesTr` is a NIfTI image representing a 3D scan. A NIfTI image stores multiple 2D slices stacked together to form a 3D volume. These 2D slices represent different anatomical sections of the liver.
- **labelsTr**: This folder contains the ground truth segmentation masks for the training data set. Each file in `labelsTr` corresponds to a specific NIfTI image in `imagesTr`. The segmentation mask is another 3D NIfTI image where each voxel (3D pixel) is labeled as either:
    - Liver tissue
    - Tumour region

Preprocessing:

Before training the model, the NIfTI images in `imagesTr` and `labelsTr` likely underwent preprocessing steps such as:

- **Normalization:** Scaling the intensity values of the images to a common range for better model performance.
- **Resampling:** Ensuring all images have the same voxel size for consistent model input.
- **Data Augmentation:** Artificially creating more training data by applying random transformations (flips, rotations) to existing images and masks. This helped improve model robustness to variations in real-world data.

- **Model performance:**

Metric	DeepLabV3Plus	MAnet	UnetPlusPlus
Training			
Loss	0.026	0.035	0.026
Pixel Accuracy	0.933	0.933	0.933
Jaccard Index	0.926	0.926	0.936
Precision	0.483	0.481	0.483
Recall	0.915	0.923	0.937
Validation			
Loss	0.025	0.036	0.028
Pixel Accuracy	0.932	0.93	0.93
Jaccard Index	0.926	0.927	0.936
Precision	0.486	0.479	0.48
Recall	0.908	0.932	0.949

Model Comparison:

- UnetPlusPlus achieved the highest training and validation Jaccard Index, indicating potentially better overlap between predicted and ground truth masks.
- UnetPlusPlus also has the highest validation recall, suggesting it captured the largest portion of actual liver pixels in unseen data.
- DeepLabV3Plus had the lowest validation loss, suggesting it might have learned the training data slightly better.
- MAnet falls between the other two models in most metrics, but has the highest validation recall

Challenges and Considerations:

- **NIfTI Data Handling:** A significant aspect of this project involved working with the NIfTI dataset format. NIfTI images store 3D medical scans, where each file represents a volume composed of multiple 2D slices.
  - **Performance vs. Accuracy Trade-off:** Due to the 3D nature of the data, processing NIfTI images can be computationally expensive compared to standard 2D images. This can lead to increased training and inference times. However, in medical image segmentation tasks like this one, accuracy is paramount. Even if processing takes longer, achieving a high degree of accuracy in tumour segmentation is crucial for real-world applications.
  - **Learning from Kaggle and External Resources:** To address the challenges of handling NIfTI data, you explored resources available on Kaggle, a platform known for data science competitions and code sharing. By studying code examples from other Kaggle users, you gained valuable insights into efficient NIfTI processing techniques. Additionally, you leveraged the informative playlist on Medical Image Analysis offered by IIT Madras on YouTube. This playlist likely provided you with a strong foundation in the specific techniques used for analyzing medical images.

Conclusion

This project successfully trained a machine learning model for liver tumour segmentation in 3D medical scans using a dataset from Kaggle. By analyzing the evaluation results, we can determine the model's effectiveness in identifying tumour regions and assess its suitability for real-world applications in clinical settings.