BME1312 Project1 Report: Deep Learning for MRI Reconstruction

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Abstract

This report details the implementation and evaluation of U-Net based deep learning models for cardiac segmentation in cine MRI scans. The project focuses on segmenting three key structures: the Left Ventricle (LV), Right Ventricle (RV), and Myocardium (MYO). We explore the standard U-Net architecture, the impact of removing skip connections, the effect of data augmentation, and the performance difference between Binary Cross-Entropy (BCE) loss and Soft Dice loss.

1 Introduction

This project aims to:

1. Implement a U-Net model for segmenting LV, RV, and MYO from cardiac cine MRI images.
2. Investigate the role of skip connections in the U-Net architecture.
3. Evaluate the impact of data augmentation on segmentation performance.
4. Compare Binary Cross-Entropy loss with Soft Dice loss for training the segmentation model.

2 Baseline U-Net

2.1 Network

The U-Net architecture consists of:

- `DoubleConv`: A block of two sequential (Conv2D 3x3, BatchNorm2D, ReLU) operations.
- `Down`: Max pooling (2x2) followed by a `DoubleConv` block for downsampling in the encoder.
- `Up`: Upsampling (bilinear or transpose convolution) followed by concatenation with features from the corresponding encoder layer (skip connection) and a `DoubleConv` block. Padding is used to handle potential size mismatches during concatenation.

Our baseline is as below:

- **Network**: The standard `UNet` class as described above, with `C_base=32`, 1 input channel, and 3 output classes. Bilinear upsampling was used.

- **Loss Function**: A custom `MyBinaryCrossEntropy` loss was used. This involves applying a Sigmoid function to the model's output logits to get probabilities, then computing `nn.BCELoss` against the 3-channel binary ground truth masks. The learning rate was 0.01.

- **Evaluation**: Mean and standard deviation of the Dice Similarity Coefficient (DSC) for LV, RV, and MYO were calculated on the test set. Training and validation loss curves were plotted by the solver. Example segmentation results were saved.

2.2 Experiments and Results

The training loss and validation loss of the baseline U-Net are shown in figure 1

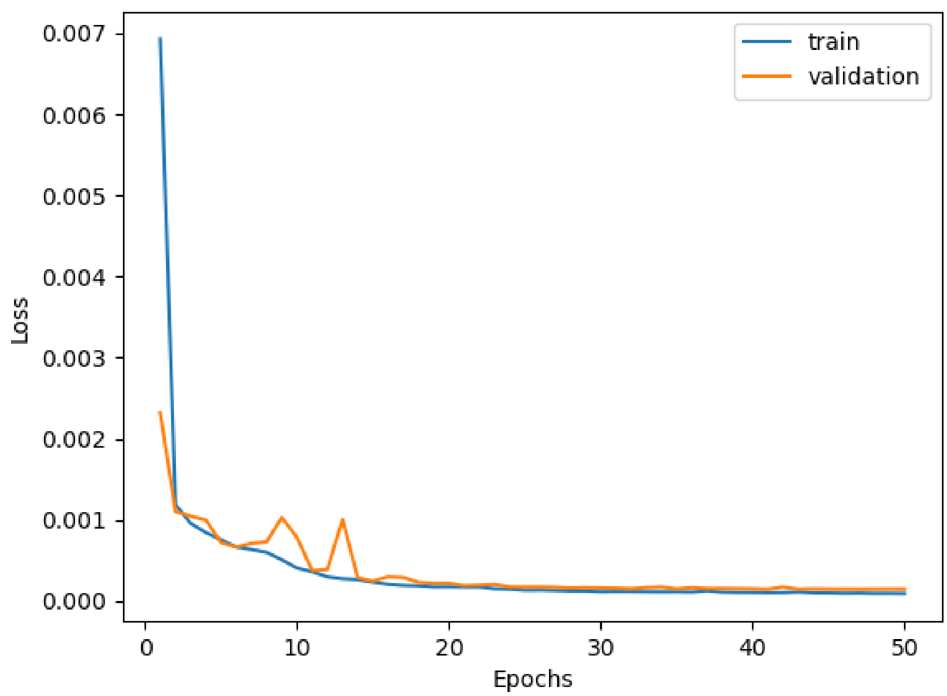

Figure 1: Training and Validation Loss Curves for the Baseline UNet

And here is an example segmentation result in figure 2

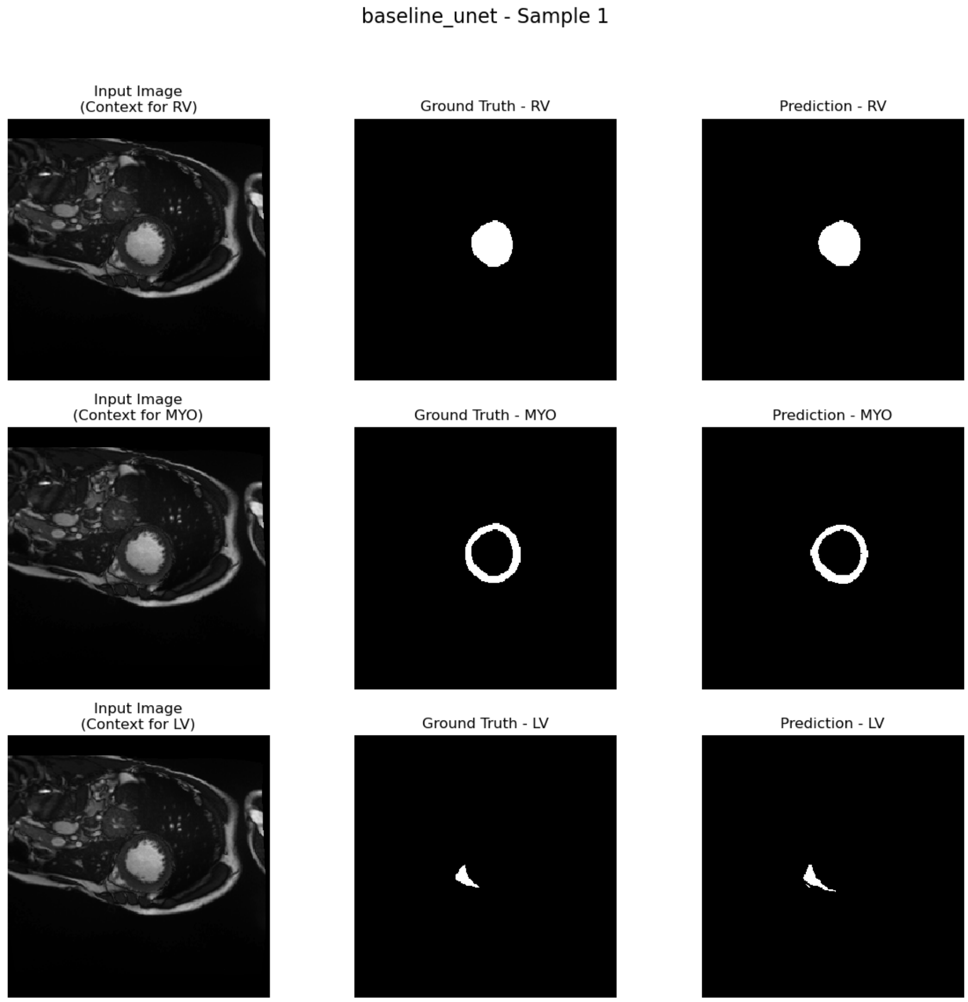

Figure 2: An Example Segmentation for the Baseline UNet

The baseline U-Net trained with Binary Cross-Entropy loss achieved the following Dice scores:

Table 1: Dice Coefficients for Baseline U-Net (Task a)

Structure	Mean Dice	Standard Deviation
RV	0.9498	0.0089
MYO	0.8755	0.0120
LV	0.8960	0.0361

2.3 Discussion

The baseline U-Net (Table 1) demonstrated strong segmentation performance.

- **RV Segmentation**: Achieved the highest mean Dice score (0.9498). This is often expected as the RV is typically a large, relatively well-defined structure with good contrast against surrounding tissues in many MRI sequences.
- **LV Segmentation**: Also showed good performance with a mean Dice of 0.8960. The LV cavity is usually clearly visible.

- **MYO Segmentation**: Had the lowest mean Dice score (0.8755). The myocardium is a thinner, more complex structure surrounding the LV, and its boundaries, especially with the LV cavity (endocardium) and epicardium, can be more challenging to delineate accurately, potentially leading to lower overlap scores.

The standard deviations are relatively small, indicating consistent performance across the test slices. Overall, the baseline U-Net provides a solid foundation for cardiac segmentation.