Deep Learning for Cardiac Cine MRI Segmentation

BME1312 Artificial Intelligence in Biomedical Imaging

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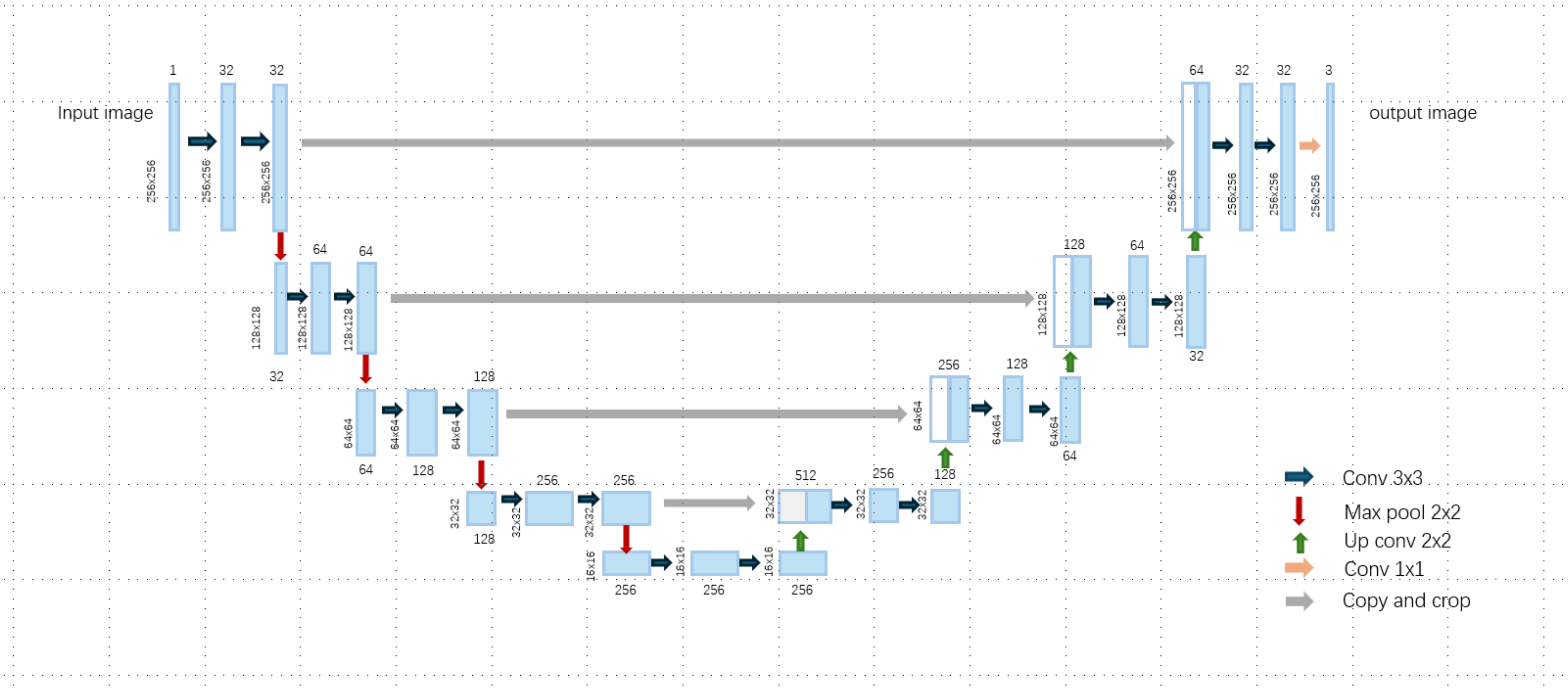
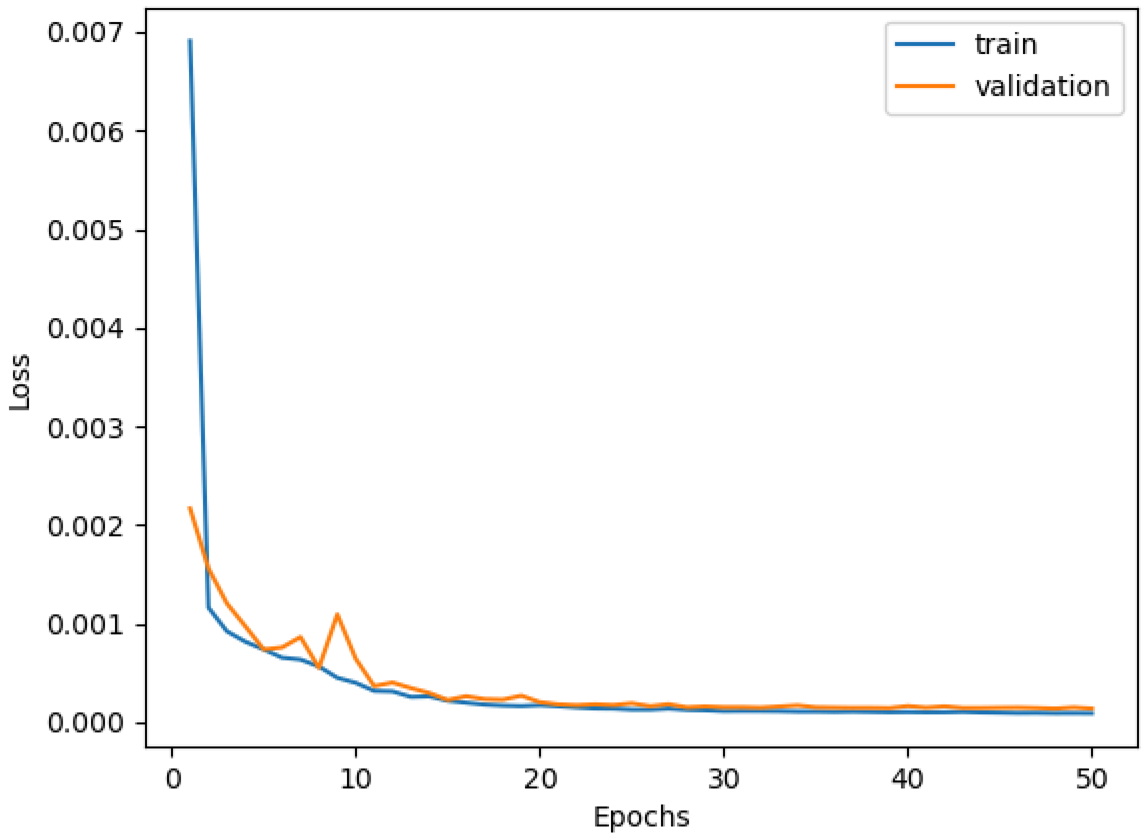
Overview

- **Goal:** Segment key cardiac structures – LV, MYO, and RV
- **Challenge:** Accurate and robust delineation of these structures, which can vary in shape and appearance.
- **Approach:** U-Net based deep learning framework.
  1. Baseline U-Net implementation.
  2. Impact of removing U-Net skip connections.
  3. Effect of data augmentation.
  4. Comparison of Binary Cross-Entropy vs. Soft Dice Loss.
  5. Improvements with Attention.
- **Evaluation:** Dice Similarity Coefficient (DSC).

Task (a): U-Net (Baseline)



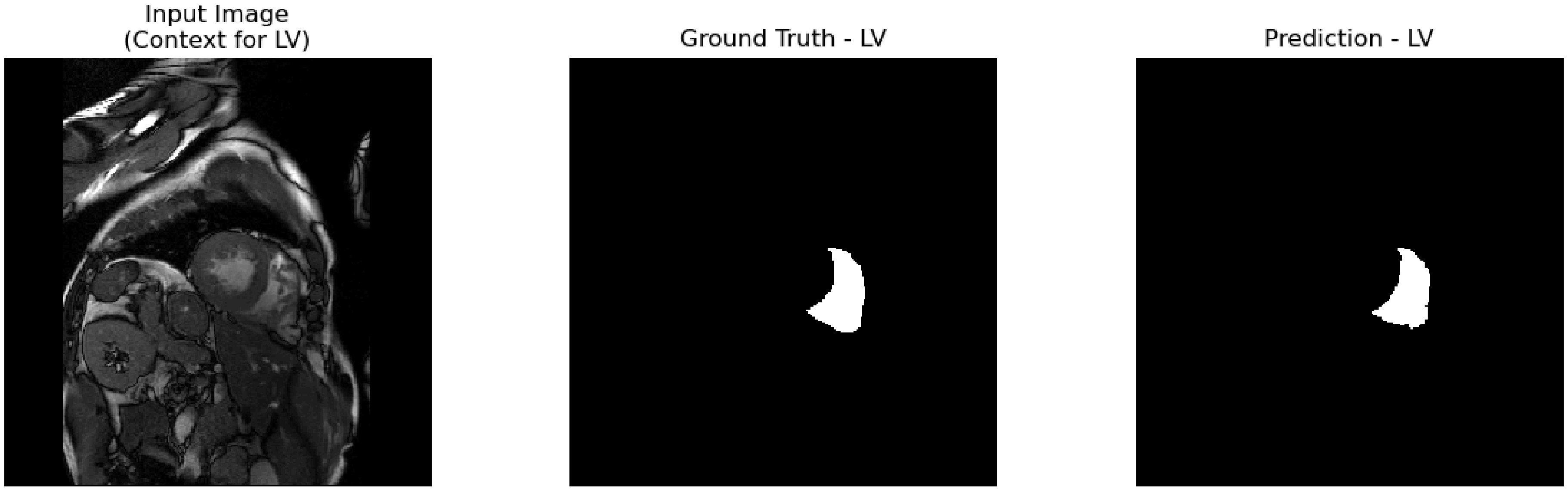
Baseline Training Loss and validation Loss



Results: Dice Coefficients

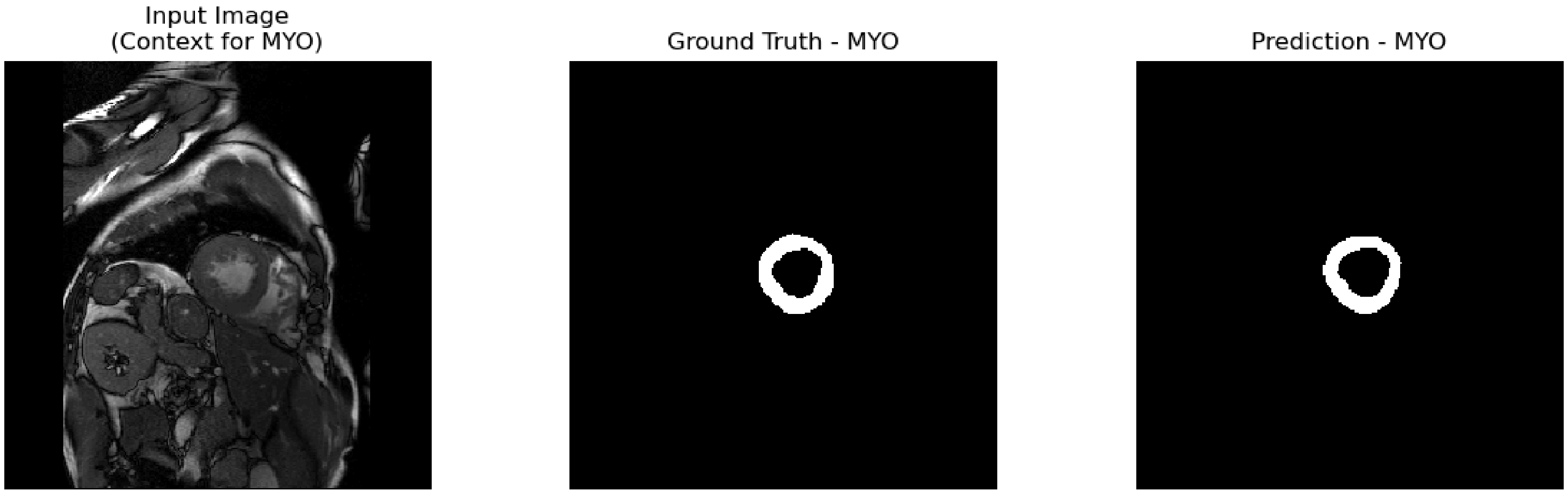
Structure	Mean Dice	Std. Dev.
RV	0.9519	0.0086
MYO	0.8734	0.0161
LV	0.8920	0.0310

Segmentation Examples (1/3)



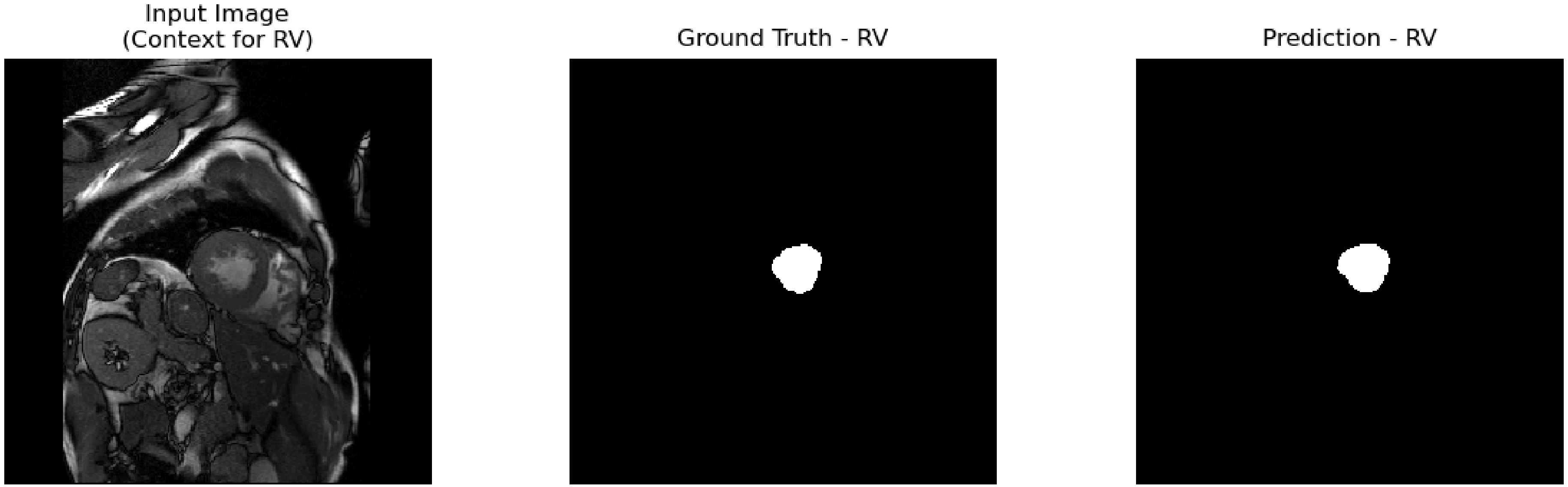
Baseline Segmentation Example LV

Segmentation Examples (2/3)



Baseline Segmentation Example MYO

Segmentation Examples (3/3)



Baseline Segmentation Example RV

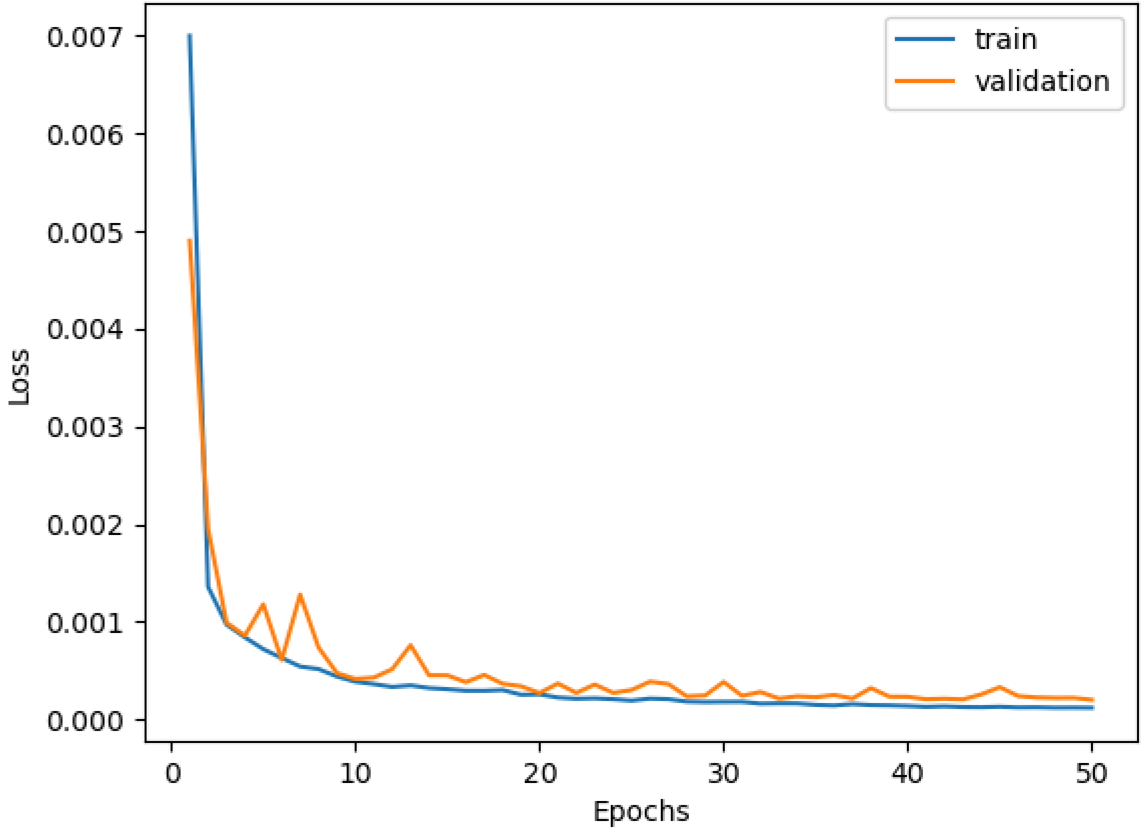
Discussion - Baseline

- **RV Segmentation**: Achieved the highest mean Dice score. 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. The LV cavity is usually clearly visible.
- **MYO Segmentation**: Had the lowest mean Dice score. 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.

Task (b): U-Net without Skip Connections

- **Modification:** No skip connections in the U-Net architecture.
- **Training:** Same as baseline (BCE Loss, lr=0.01, 50 epochs).
- **Purpose:** Evaluate the importance of skip connections.

Training Loss and validation Loss (No Short-cut)



Training and Validation Loss for Baseline U-Net without shortcut.

Results: Dice Coefficients

Structure	Baseline DSC	No Shortcut DSC
RV Mean	**0.9519**	0.9260
MYO Mean	**0.8734**	0.8223
LV Mean	**0.8920**	0.8588
RV std	0.0086	0.0111
MYO std	0.0161	0.0168
LV std	0.0310	0.0296

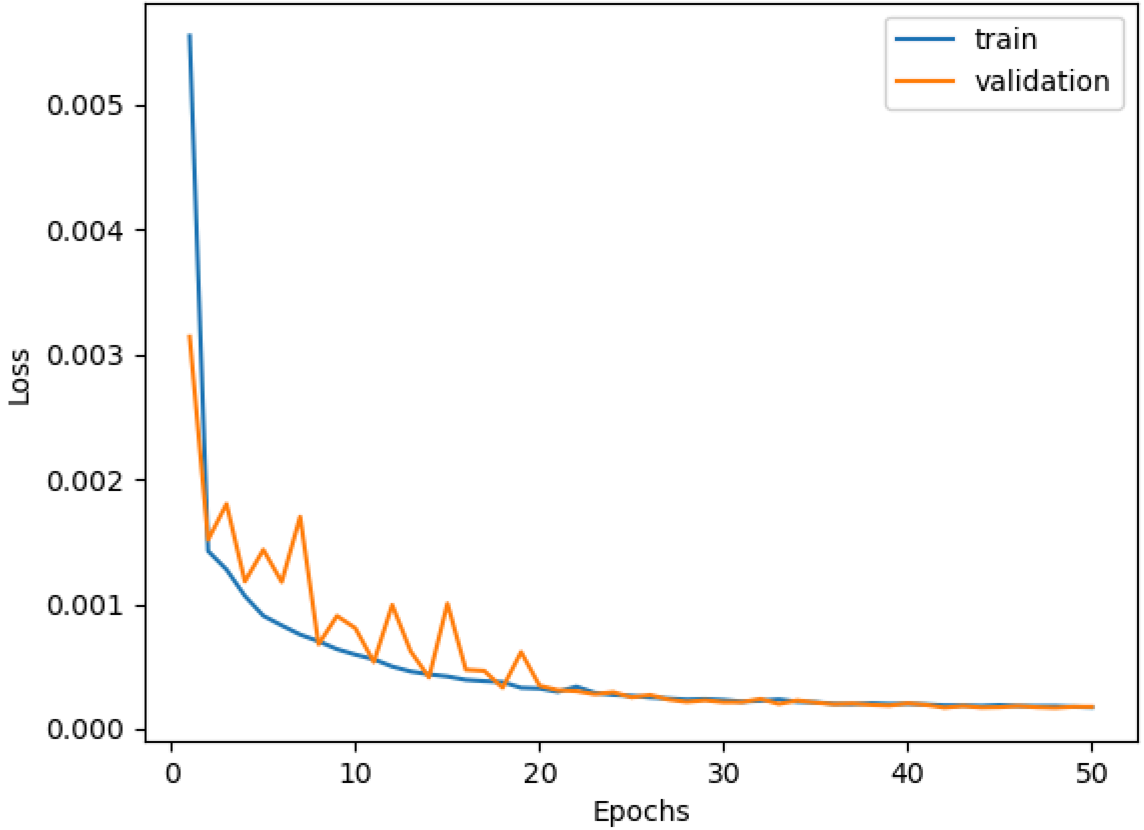
Discussion - Impact of No Skip Connections

- **Significant Drop in Performance:** All structures showed a noticeable decrease in DSC.
- **Reason:** Skip connections provide high-resolution spatial information from the encoder to the decoder, crucial for accurate boundary localization. They also aid gradient flow.
- **Conclusion:** Skip connections are vital for U-Net's segmentation accuracy in this task.

Task (c): U-Net with Data Augmentation

- **Network:** Baseline U-Net architecture.
- **Augmentations (Training Set Only):**
  - `RandomHorizontalFlip`, `RandomRotation(15°)`,
  - `RandomAffine(degrees=50, translate=(0.1,0.1), scale=(0.9,1.1), shear=5)`.
- **Implementation:** `SegmentationDataset` ensuring identical transforms for image and mask.
- **Training:** BCE Loss, lr=0.01, 50 epochs.

Training Loss and validation Loss (with Data Augmentation)



Training and Validation Loss for Baseline with Data Augmentation.

Results: Dice Coefficients

Structure	Baseline DSC	Data Aug. DSC
RV Mean	**0.9519**	0.9276
MYO Mean	**0.8734**	0.8469
LV Mean	**0.8920**	0.8635
RV std	0.0086	0.0107
MYO std	0.0161	0.0149
LV std	0.0310	0.0384

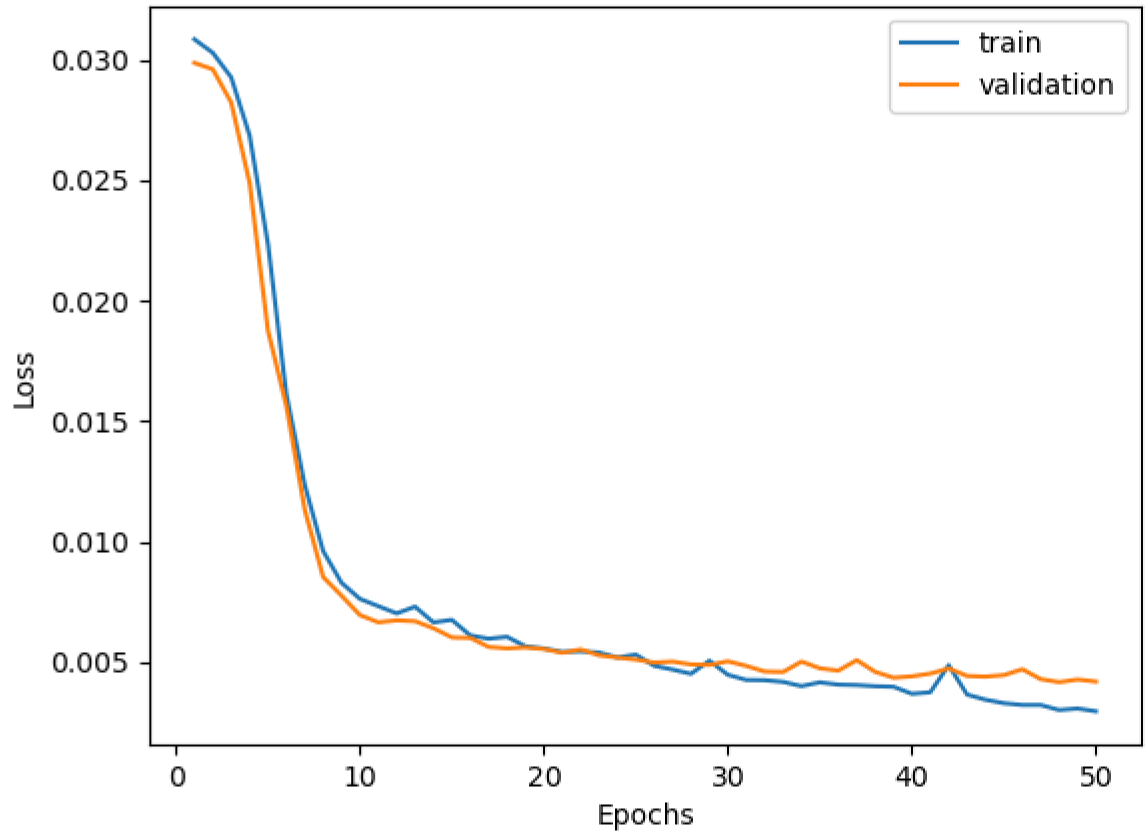
Discussion - Impact of Data Augmentation

- **DSC Decrease:** The specific augmentation strategy led to slightly lower Dice scores.
- **Possible Reasons:**
  - Some augmentations could have distorted anatomical structures, reducing the effectiveness of learning precise boundaries. Maybe the relative location of structures was altered too much.
- **Conclusion:** The relative location of structures is crucial for segmentation tasks, and the specific augmentations used may not have been beneficial for this dataset. More careful selection or tuning of augmentations is needed.

Task (d): U-Net with Soft Dice Loss

- **Network:** Baseline U-Net architecture.
- **Training Data:** Original Non-Augmented Training Set (The best).
- **Loss Function:** `SoftDiceLoss`
- **Optimizer:** Adam (lr=0.001), ExponentialLR scheduler.
- **Training:** 50 epochs.

Training Loss and validation Loss (With Soft Dice Loss)

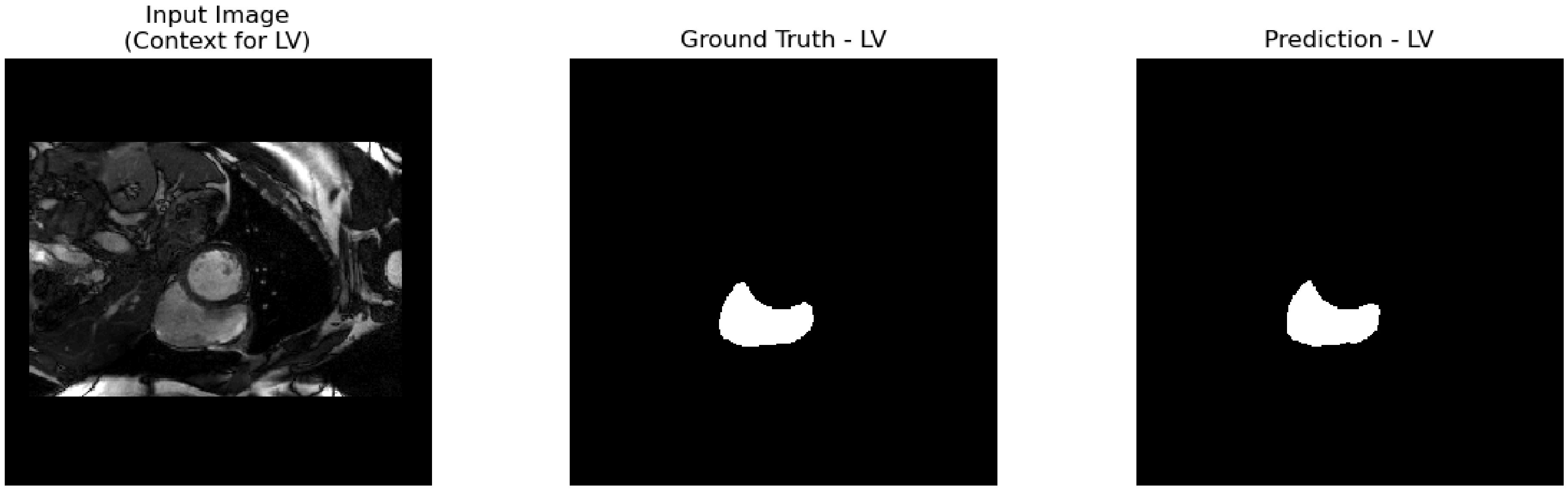


Training and Validation Loss for Baseline with Soft Dice Loss.

Results: Dice Coefficients

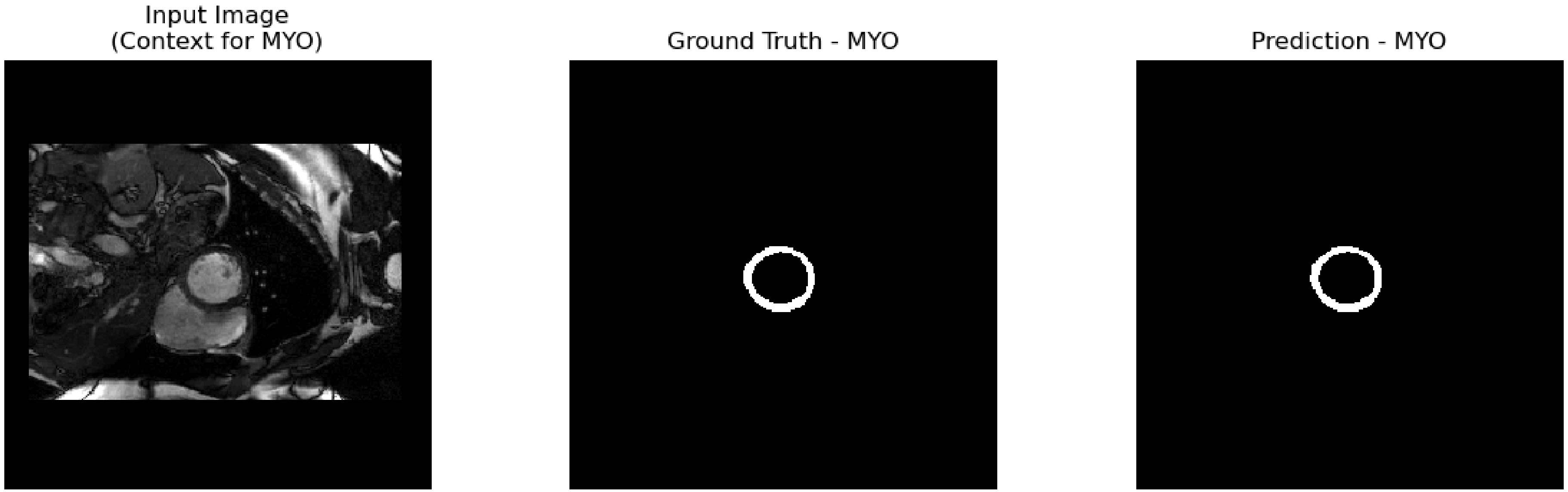
Structure	Baseline with BCE Loss	Baseline with Soft Dice Loss
RV Mean	0.9519	**0.9566**
MYO Mean	0.8734	**0.8962**
LV Mean	0.8920	**0.8998**
RV std	0.0086	0.0100
MYO std	0.0161	0.0100
LV std	0.0310	0.0371

Segmentation Examples (1/3)



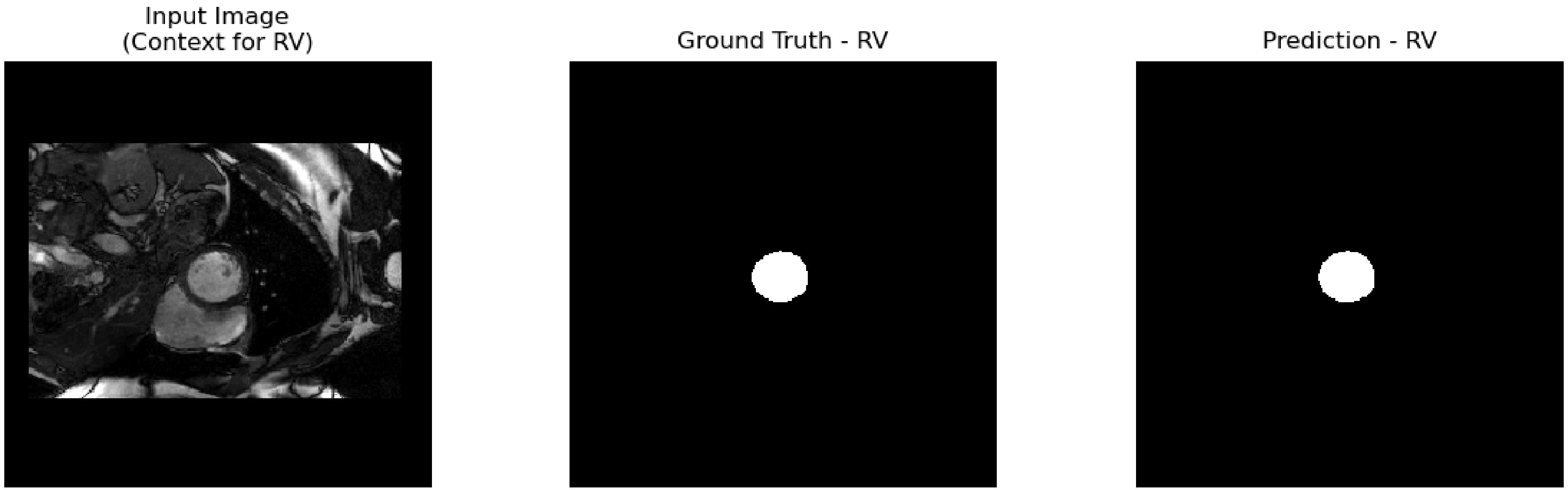
Baseline with Soft Dice Loss Segmentation Example LV

Segmentation Examples (2/3)



Baseline with Soft Dice Loss Segmentation Example MYO

Segmentation Examples (3/3)



Baseline with Soft Dice Loss Segmentation Example RV

Discussion - Soft Dice Loss

- When trained on the same non-augmented data, **Soft Dice Loss significantly outperformed BCE Loss** in terms of Dice Coefficient for all structures.
- The improvement is most notable for MYO segmentation.
- This suggests that directly optimizing a Dice-based metric is beneficial for this segmentation task.

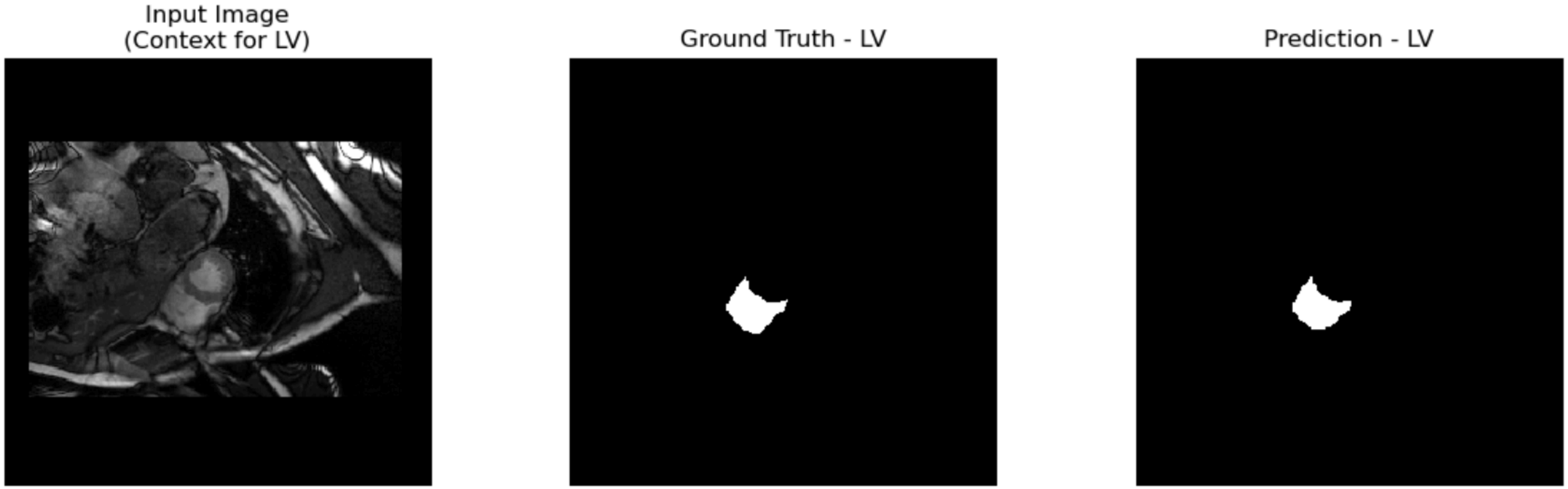
Task (e): Improvements

- **Advanced UNet (Attention U-Net):**
- **Architecture:** Introduced `AttentionBlock` in the decoder's `Up` module.
  * `AttentionBlock`: Computes attention coefficients by combining features from the decoder (gating signal) and encoder (skip connection), then applies these coefficients to the encoder features. This helps the model focus on relevant spatial regions during upsampling.
- **Loss Function:** `Soft Dice Loss`.
- **Optimizer:** Adam (lr=0.001), ExponentialLR scheduler.
- **Training:** 50 epochs.

Results: Dice Coefficients

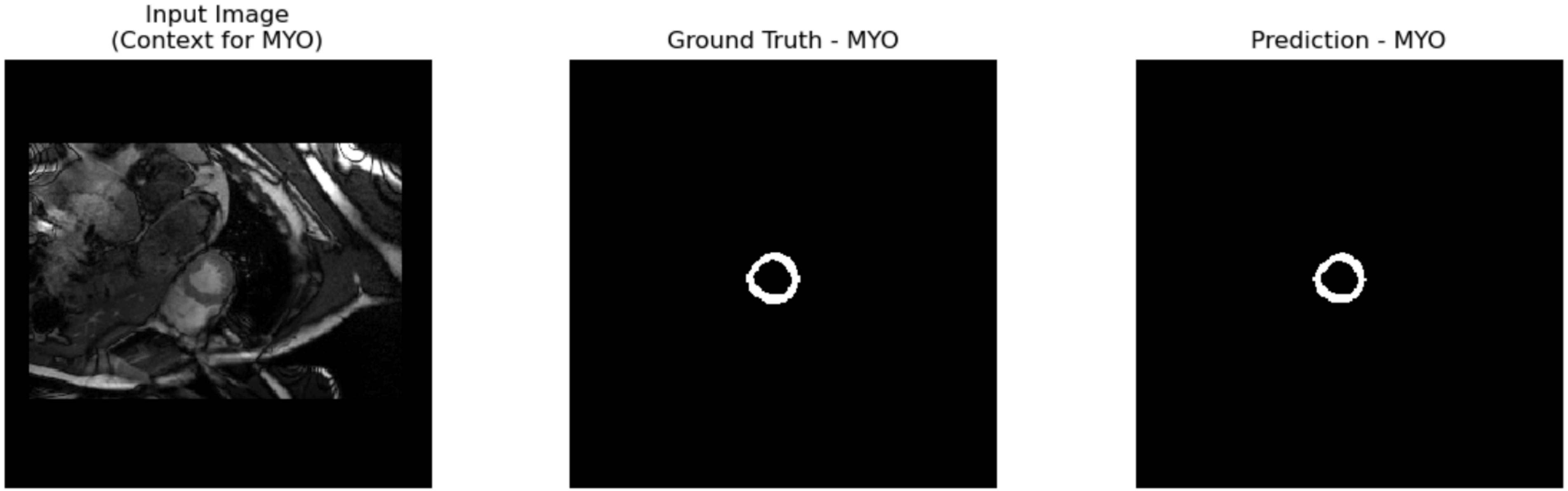
Structure	Baseline with BCE Loss	Baseline with Soft Dice Loss	Attention U-Net
RV Mean	0.9519	0.9566	**0.9588**
MYO Mean	0.8734	0.8962	**0.8967**
LV Mean	0.8920	0.8998	**0.9072**
RV std	0.0086	0.0100	0.0086
MYO std	0.0161	0.0100	0.0109
LV std	0.0310	0.0371	0.0292

Segmentation Examples (1/3)



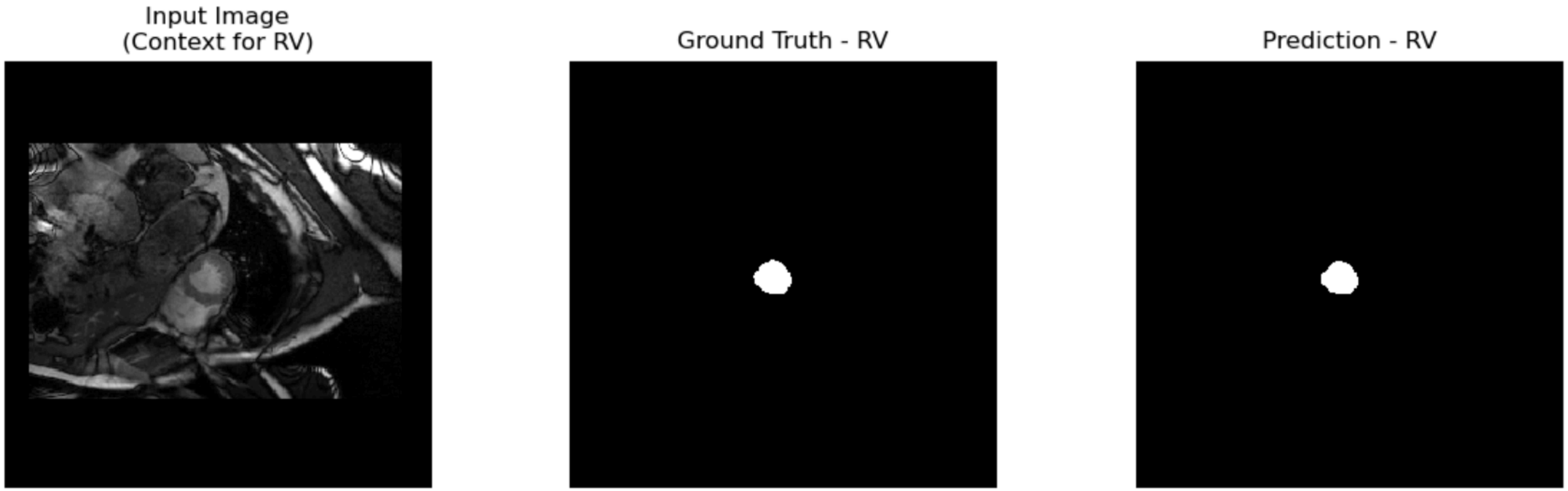
Attention U-Net Segmentation Example LV

Segmentation Examples (2/3)



Attention U-Net Segmentation Example MYO

Segmentation Examples (3/3)



Attention U-Net Segmentation Example RV

Discussion - Attention U-Net

- The Attention U-Net showed improved Dice scores compared to the baseline U-Net with BCE loss and the one with Soft Dice Loss.
- This suggests that the attention mechanism effectively helps the model to focus on more complex structures or finer details, leading to better boundary delineation.
- Accuracy scores are very high across all structures, which is common in segmentation tasks with large background areas. Dice coefficient remains a more informative metric for evaluating overlap.

Overall Performance Summary (Dice Coefficients)

Model	RV Mean DSC	MYO Mean DSC	LV Mean DSC
(a) Baseline U-Net (BCE)	0.9519	0.8734	0.8920
(b) U-Net No Shortcut (BCE)	0.9260	0.8223	0.8588
(c) U-Net + Data Aug. (BCE)	0.9276	0.8469	0.8635
(d) U-Net (Soft Dice Loss)	0.9566	0.8962	0.8998
(e) Attention U-Net (Soft Dice Loss)	**0.9588**	**0.8967**	**0.9072**

Conclusion & Future Work

- **Key Findings:**
  - U-Net with **Soft Dice Loss (trained on non-augmented data) yielded the best segmentation performance** (Dice scores).
  - Skip connections are crucial.
  - The specific data augmentation strategy tested did not improve Dice scores over the baseline non-augmented models.

Thanks!