Deep Learning for Cardiac Cine MRI Segmentation

BME1312 Artificial Intelligence in Biomedical Imaging

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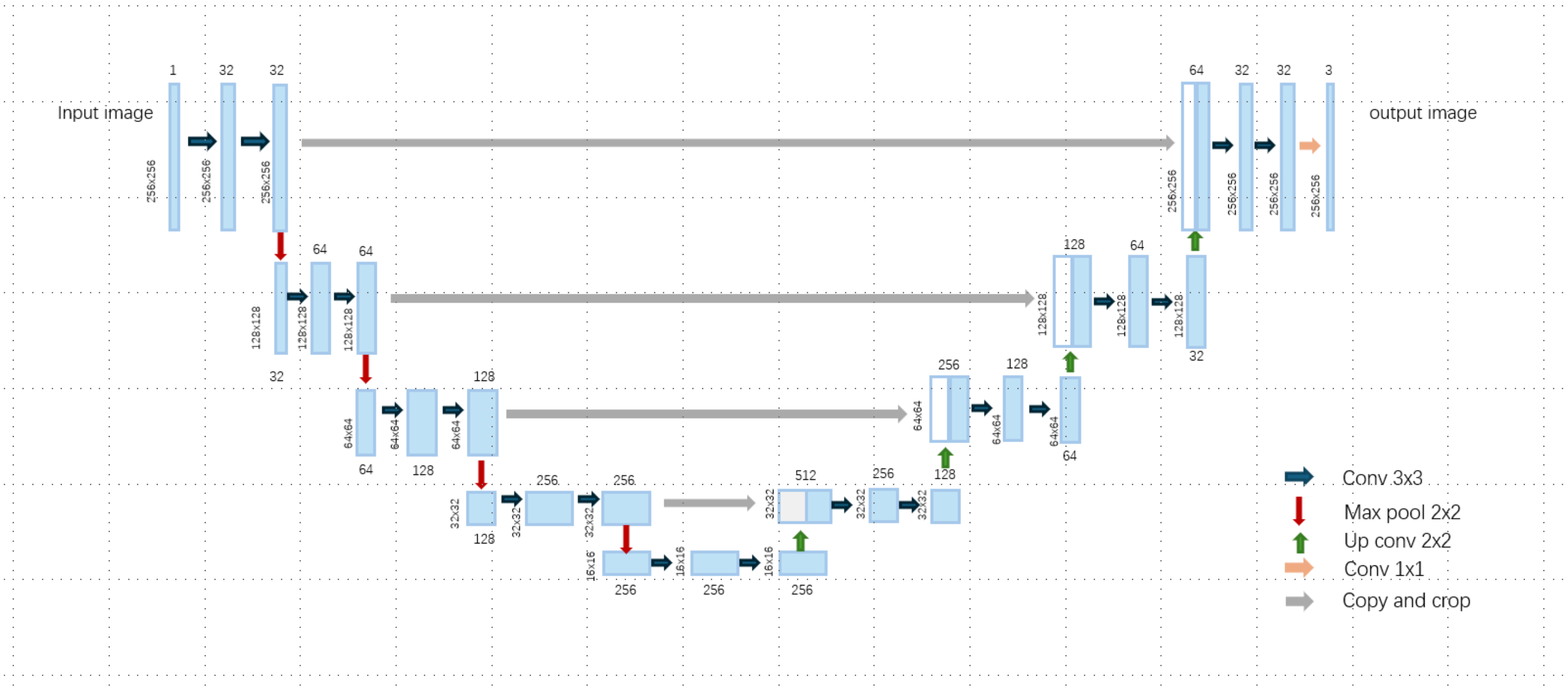
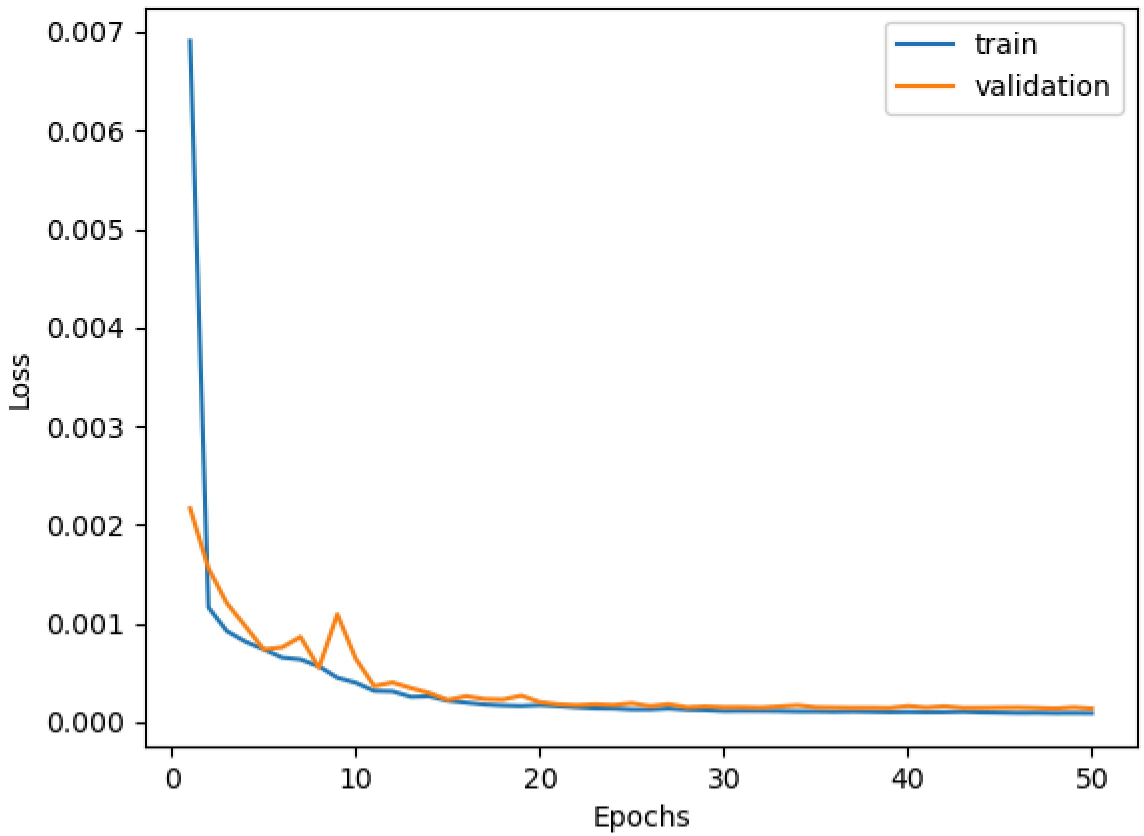
Overview

- **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.
    - Baseline U-Net implementation.
    - Impact of removing U-Net skip connections.
    - Effect of data augmentation.
    - Comparison of Binary Cross-Entropy vs. Soft Dice Loss.
    - Improvements with Attention.
- **Evaluation:** Dice Similarity Coefficient (DSC).

Task (a): U-Net (Baseline)



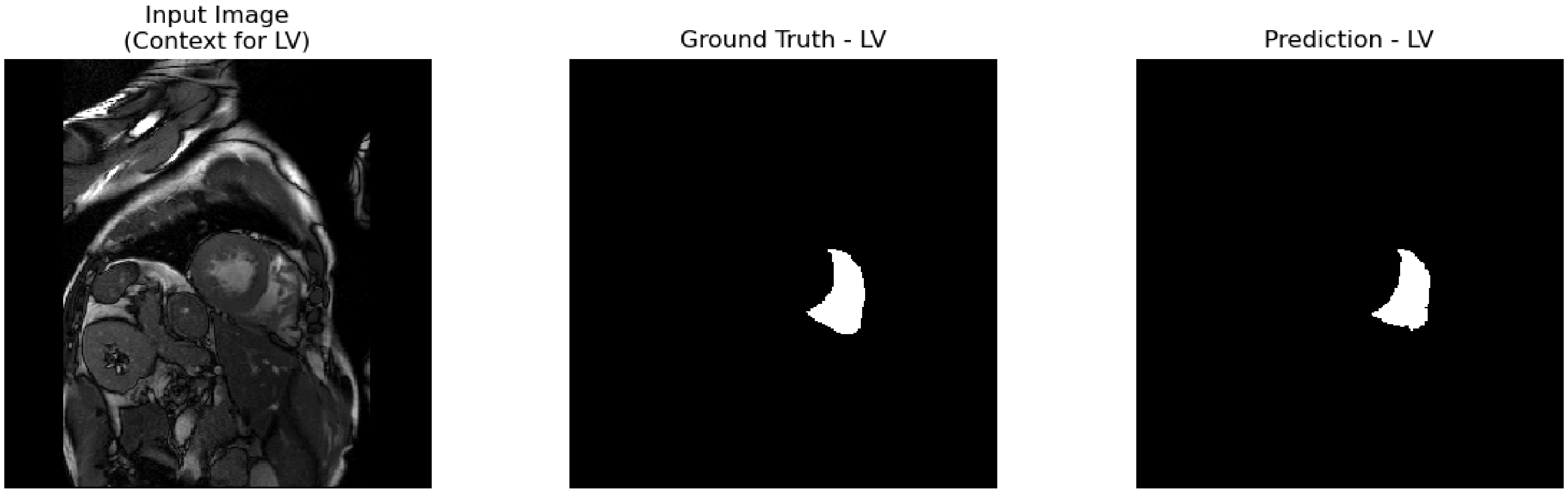
Baseline Training Loss and validation Loss



Results: Dice Coefficients

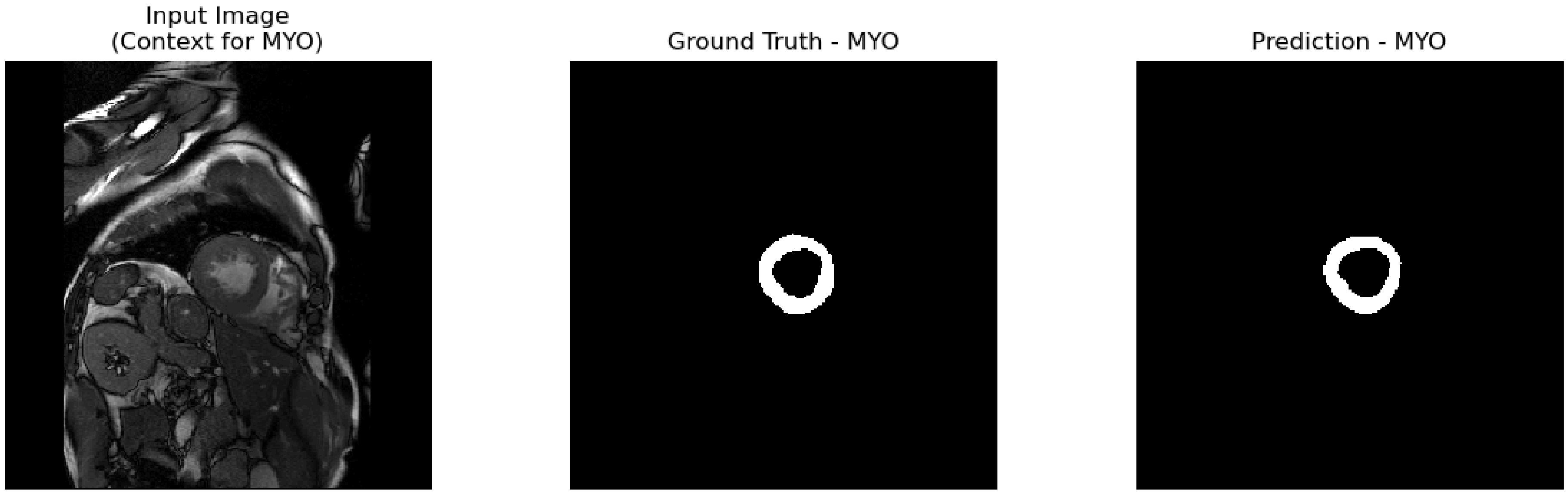
Structure	Mean Dice	Std. Dev.
RV	0.9519	0.0086
MYO	0.8734	0.0161
LV	0.8920	0.0310

Segmentation Examples (1/3)



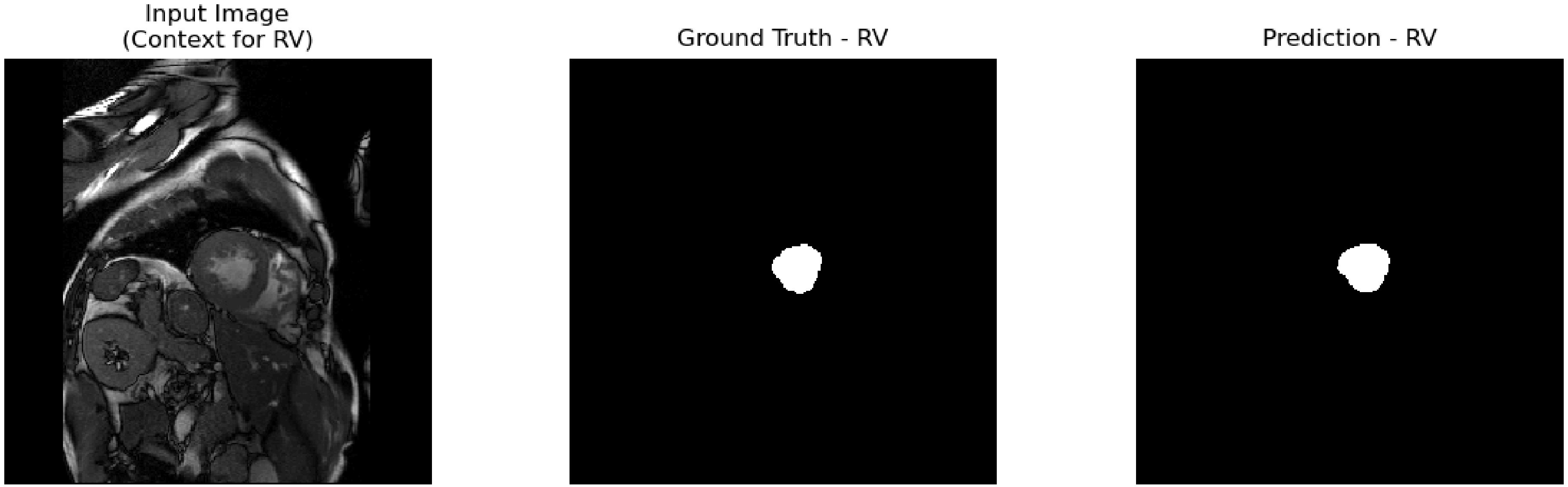
Baseline Segmentation Example LV

Segmentation Examples (2/3)



Baseline Segmentation Example MYO

Segmentation Examples (3/3)



Baseline Segmentation Example RV

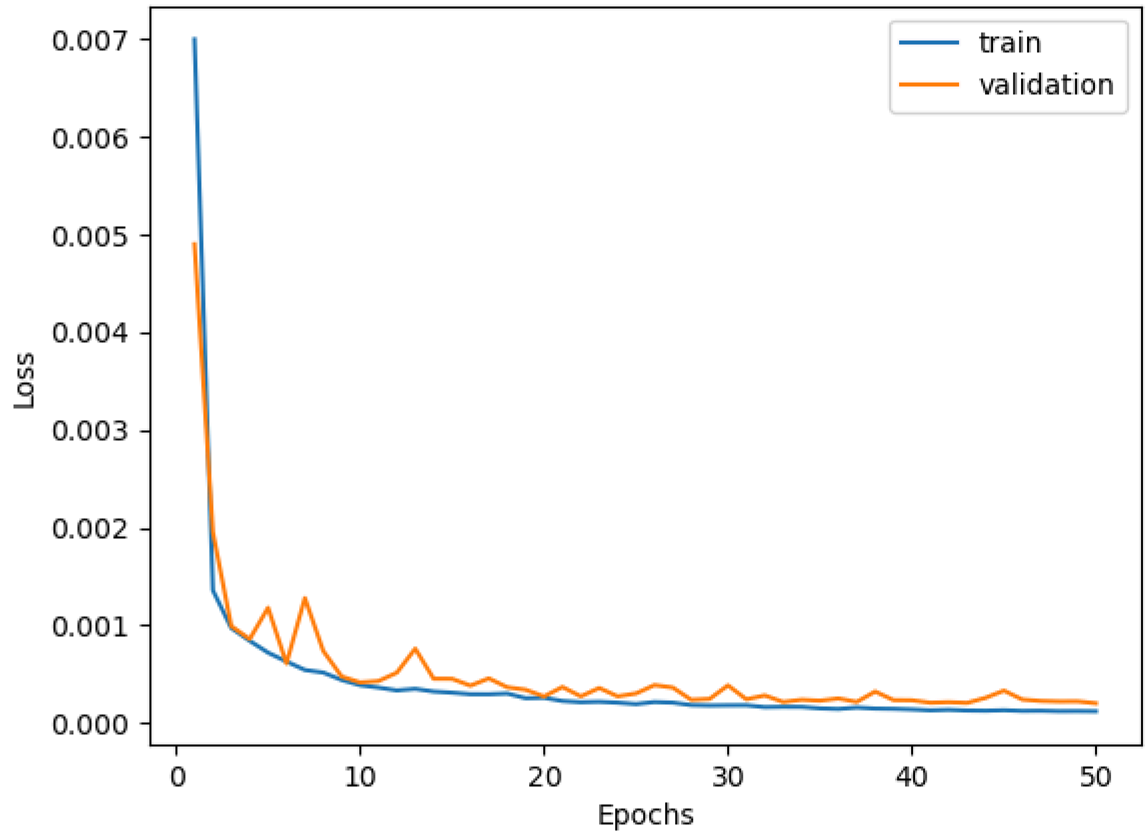
Discussion - Baseline

- **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

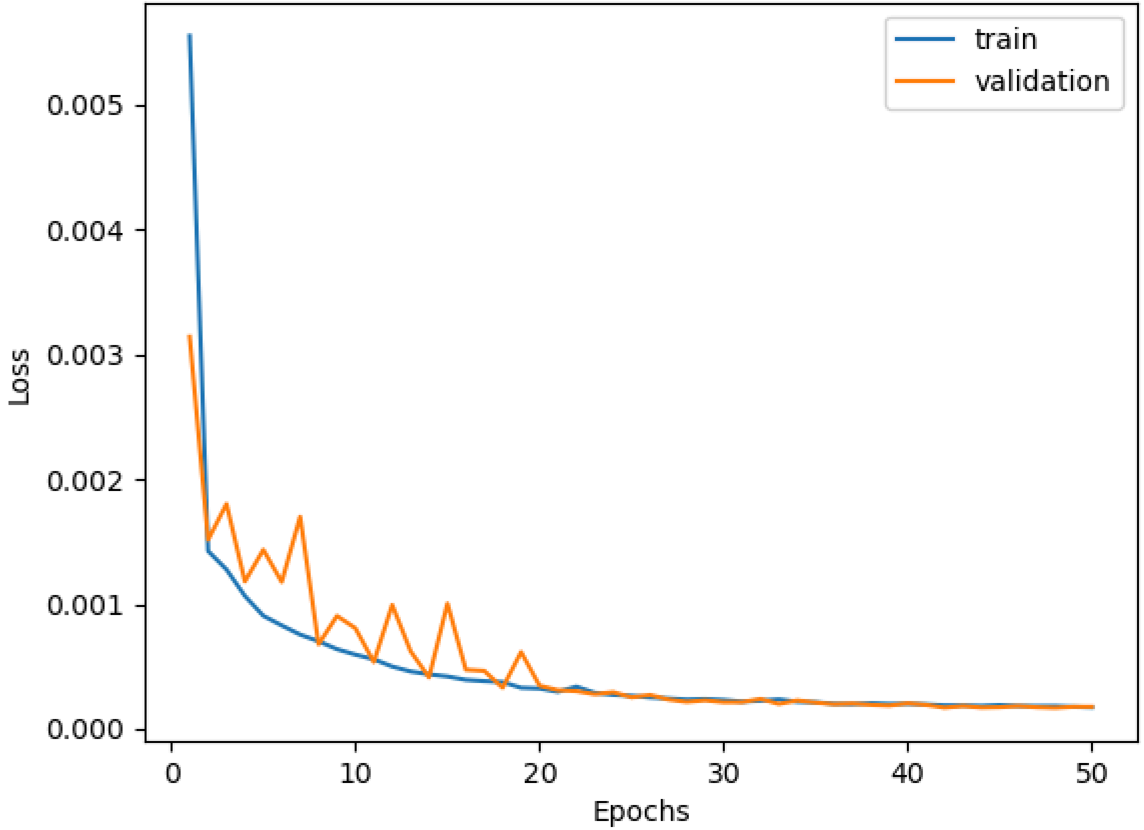
Discussion - Impact of No Skip Connections

- **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

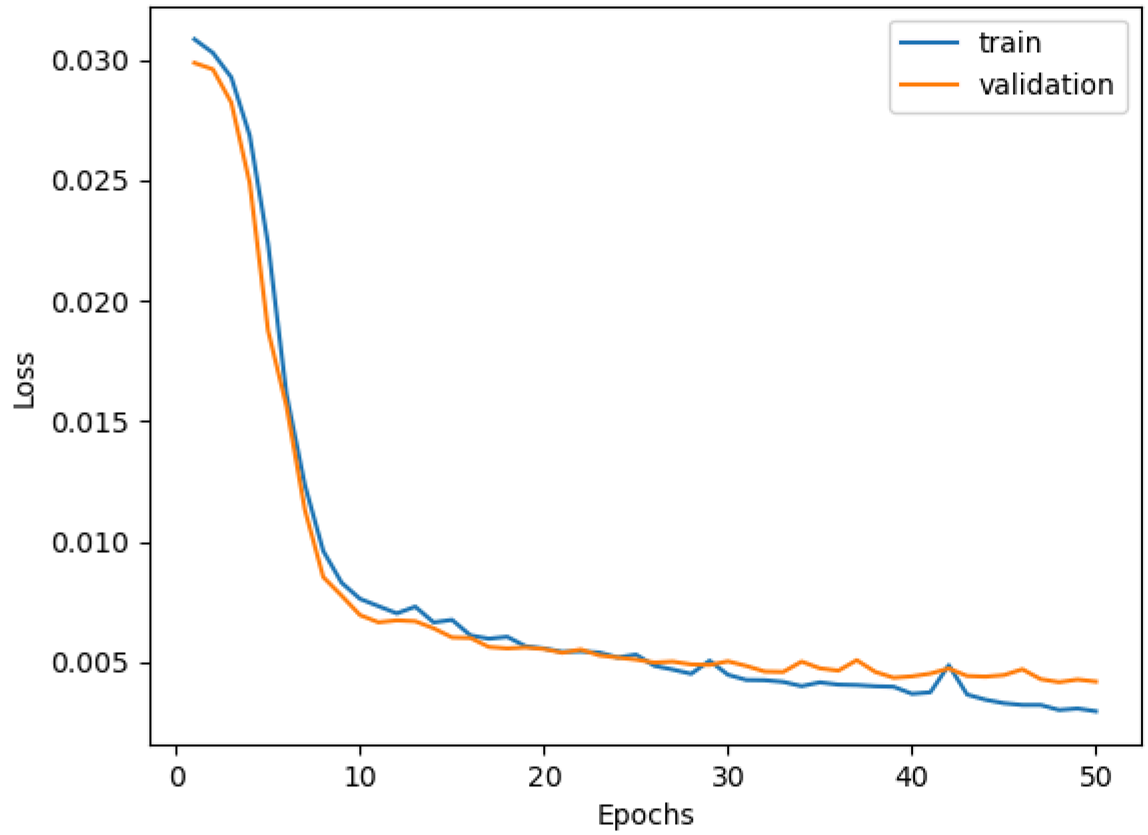
Discussion - Impact of Data Augmentation

- **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.

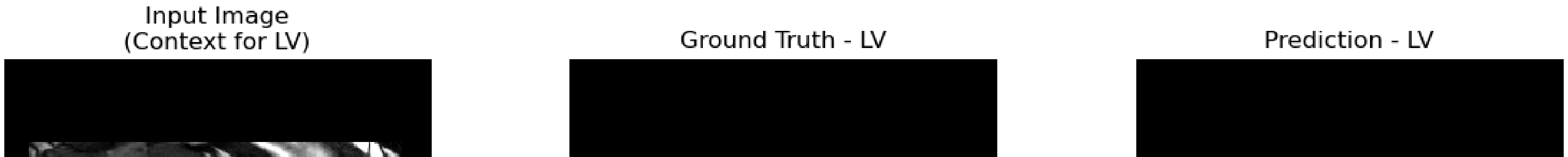
Results: Dice Coefficients

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

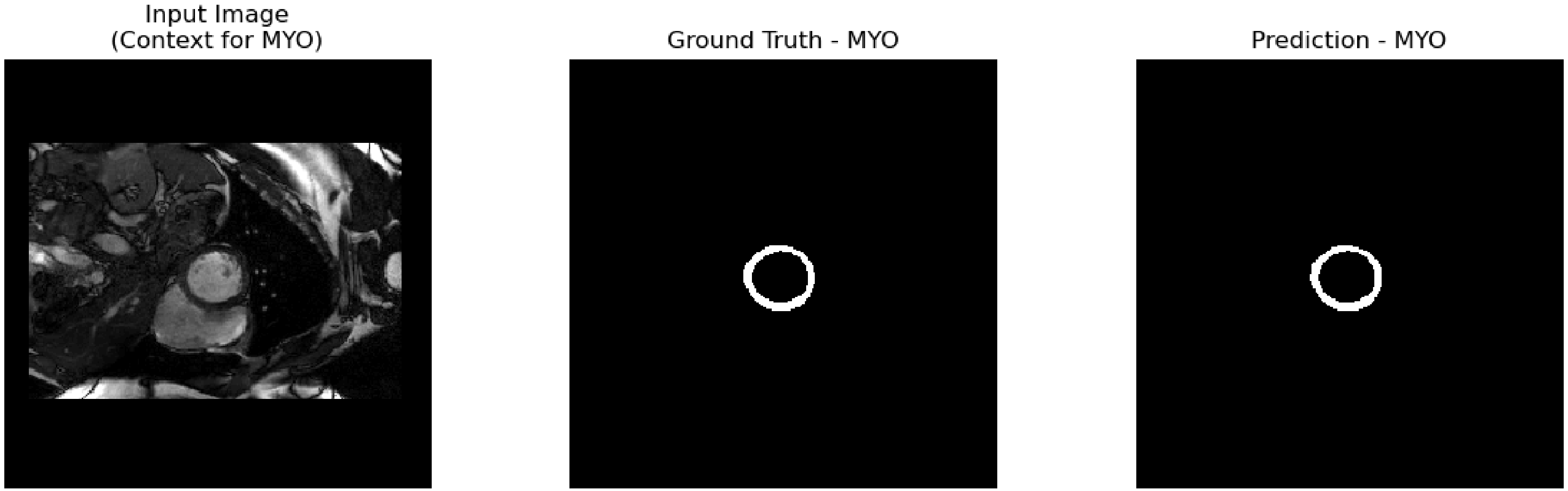
Results: Accuracy

Structure	Baseline with BCE Loss	Baseline with Soft Dice Loss
RV Accuracy Mean	0.9991	**0.9992**
MYO Accuracy Mean	0.9977	**0.9980**
LV Accuracy Mean	0.9983	0.9983
RV Accuracy std	0.0002	0.0002
MYO Accuracy std	0.0003	0.0002
LV Accuracy std	0.0005	0.0006

Segmentation Examples (1/3)

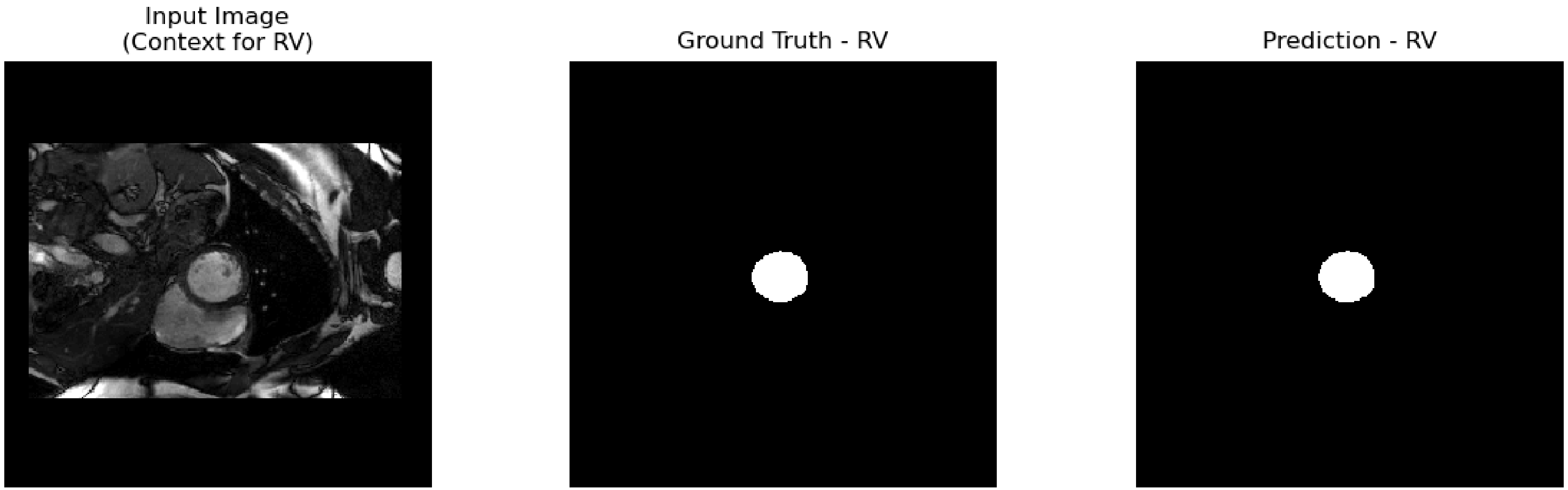


Segmentation Examples (2/3)



Baseline with Soft Dice Loss Segmentation Example MYO

Segmentation Examples (3/3)



Baseline with Soft Dice Loss Segmentation Example RV

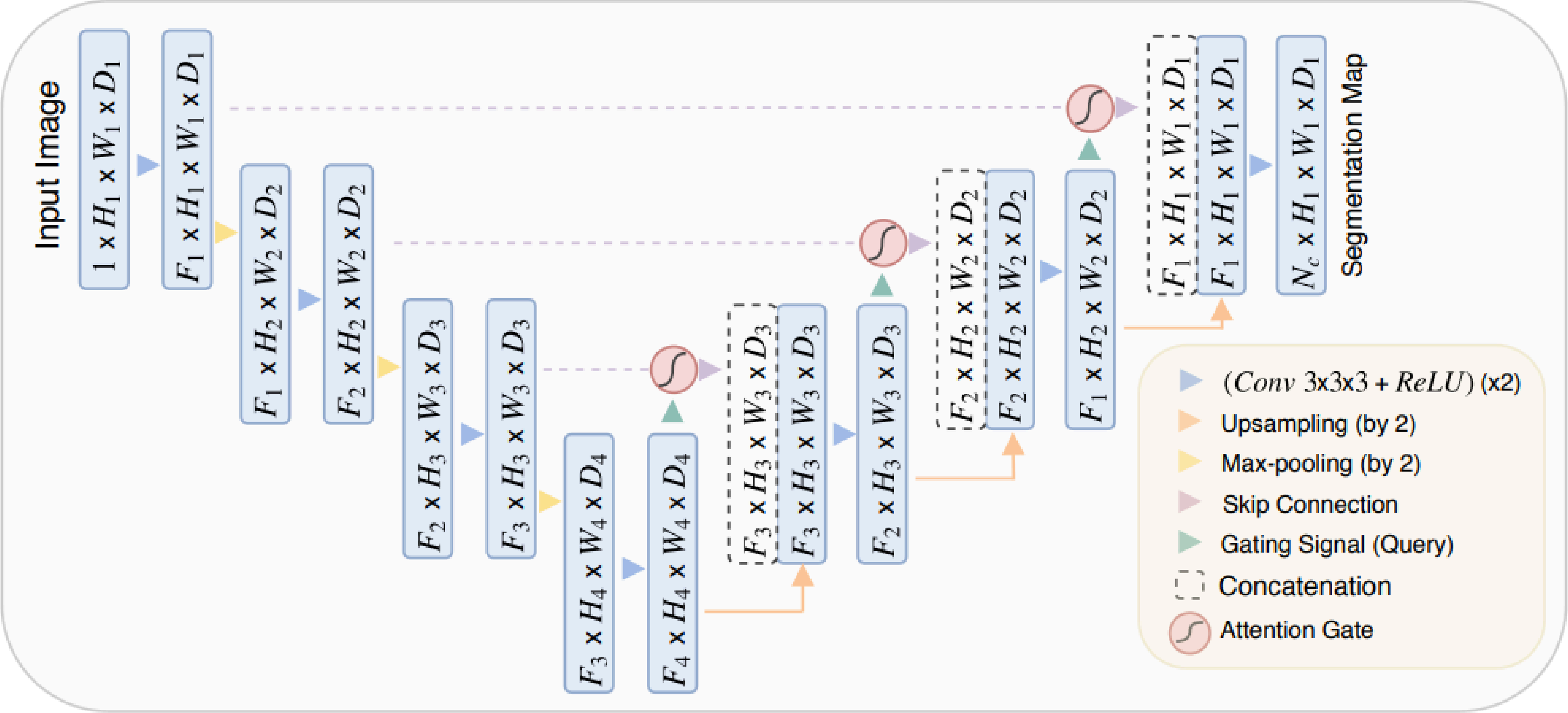
Discussion - Soft Dice Loss

- **Segmentation Accuracy (Dice):** Using Soft Dice Loss resulted in **noticeably better Dice coefficients** for all cardiac structures compared to BCE Loss when trained on the same non-augmented data. The improvement for MYO was particularly significant.
- **Segmentation Accuracy (Pixel-wise):** Pixel-wise accuracy also showed slight improvements or remained comparable at very high levels.
- **Conclusion for Task (d):** Changing the training loss from cross-entropy (BCE) to Soft Dice Loss **improved overall segmentation accuracy**, especially when evaluated by the Dice coefficient, which is more sensitive to segmentation overlap.

Task (e): Improvements - Part One

- **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.

Attention U-Net

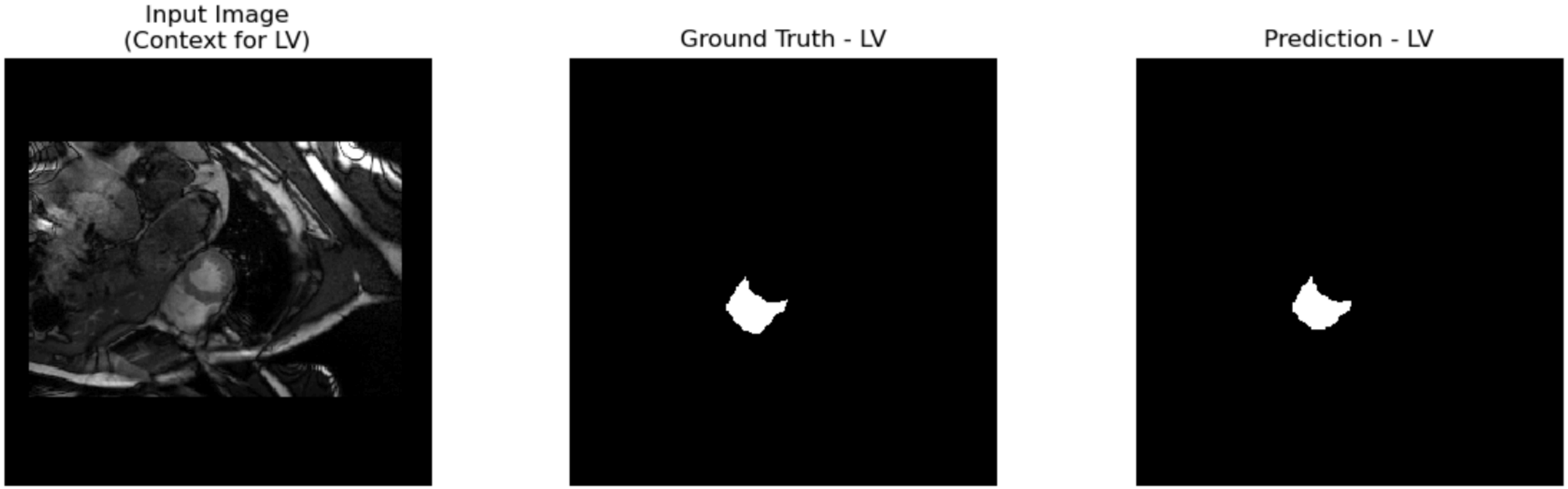


Attention U-Net

Results: Dice Coefficients

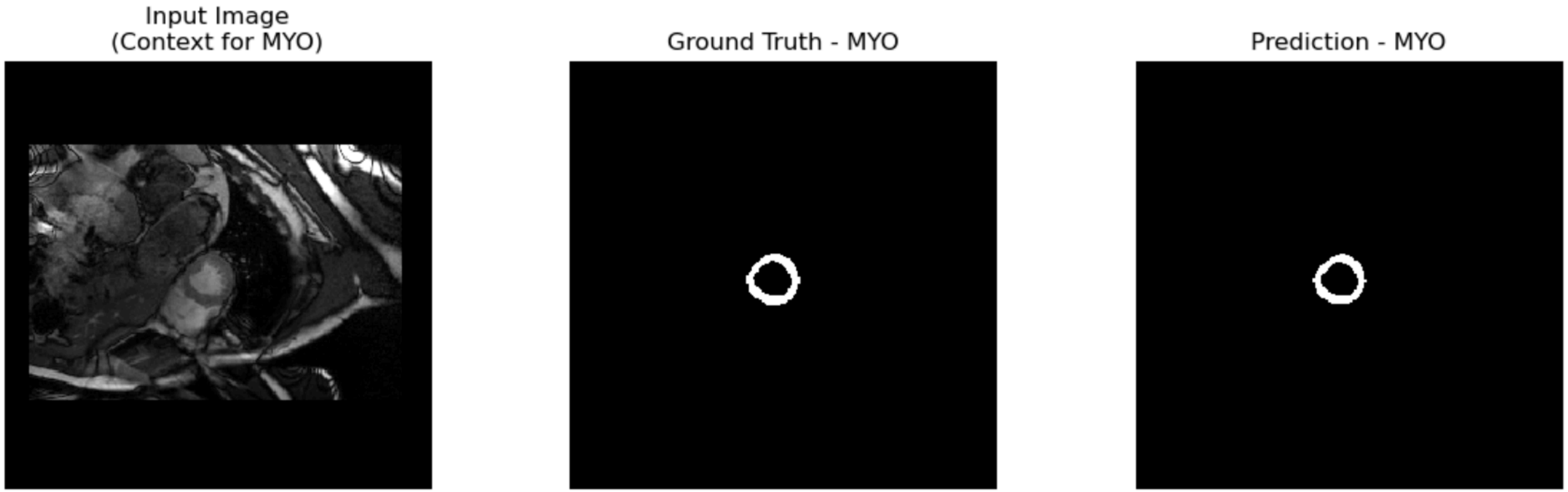
Structure	Baseline with BCE Loss	Baseline with Soft Dice Loss	Attention U-Net
RV Mean	0.9519	0.9566	**0.9588**
MYO Mean	0.8734	0.8962	**0.8967**
LV Mean	0.8920	0.8998	**0.9072**
RV std	0.0086	0.0100	0.0086
MYO std	0.0161	0.0100	0.0109
LV std	0.0310	0.0371	0.0292

Segmentation Examples (1/3)



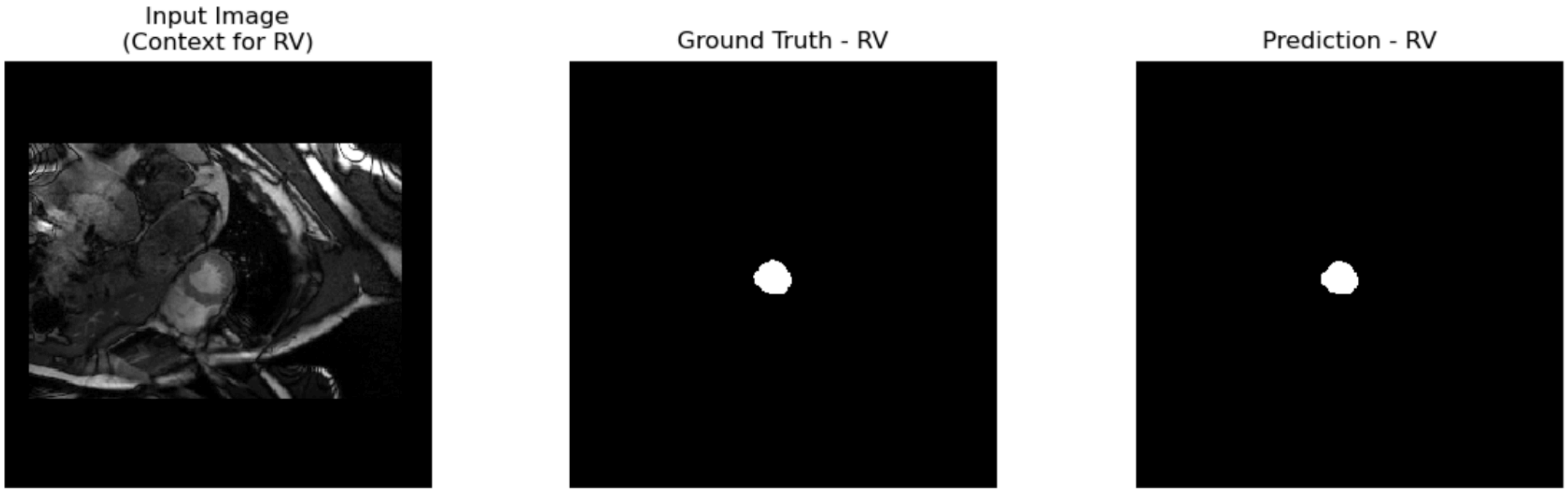
Attention U-Net Segmentation Example LV

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.

Task (e): Improvements - Part Two

Motivation:

To further improve segmentation, especially at boundaries and for complex structures, by combining multiple complementary loss objectives. This aims to leverage the strengths of different loss types for a more holistic optimization.

HybridLoss

The HybridLoss adaptively weights four distinct loss components:

1. **Dice Loss** (Overlap)
2. **Binary Cross-Entropy (BCE) Loss** (Pixel-wise accuracy)
3. **Boundary Loss** (Edge definition)
4. **Hausdorff Distance Loss (Approximation)** (Shape similarity)

- Features adaptive weighting of these components using learnable uncertainty parameters.

Task (e): Results with HybridLoss (Mean Dice Scores)

Model	RV Dice (SD)	MYO Dice (SD)	LV Dice (SD)
UNet + HybridLoss	0.9504 (0.0276)	0.8839 (0.0275)	0.9061 (0.0573)
Baseline U-Net	*0.9519*	*0.8734*	*0.8920*
AttUNet + HybridLoss	0.9507 (0.0235)	0.8875 (0.0247)	0.9033 (0.0703)
Attention U-Net	*0.9588*	*0.8967*	*0.9072*

Updated Overall Performance Summary (Mean Dice Scores)

Model Configuration	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, No Aug.)	**0.9566**	**0.8962**	0.8998
(e1) UNet + HybridLoss	0.9504	0.8839	**0.9061**
(e2) AttUNet + HybridLoss	0.9507	0.8875	0.9033

Discussion

- The **U-Net with Soft Dice Loss (Task d)** remains the top performer for RV and MYO segmentation.
- Models utilizing **UNet + HybridLoss (Task e1)**, achieved the best LV Dice score.
- **No Universal Superiority:** HybridLoss, despite its sophisticated multi-component design with adaptive weighting, did not prove to be a universally superior loss function in these experiments.
- **LV Segmentation Strength:** A consistent observation is the relative strength of HybridLoss (or its components) in improving or maintaining high performance for LV segmentation, even when RV/MYO performance drops.

Conclusion

- **Best Overall Performance (Structure-wise):**
  - **RV & MYO:** U-Net with Soft Dice Loss (Task d) shows the highest Dice scores.
  - **LV:** U-Net (and AttUNet) with HybridLoss (Task e) achieves the best Dice scores.
- **Complexity vs. Simplicity:** A simpler model (U-Net) with a well-chosen, targeted loss function (Soft Dice Loss) can still be highly effective and may outperform more complex loss formulations on certain structures or metrics.
- The performance of HybridLoss models suggests that further optimization (e.g., training duration, hyperparameter tuning of the loss components or solver) could potentially lead to even better results.

Thanks!