# PROJECT WORK

## Medical Imaging

**Prof. Tortorella Francesco**
**Phd Mattia Sarno**

UNIVERSITÀ DEGLI STUDI DI SALERNO

# Enhancing Liver Segmentation Across Medical Imaging Modalities

## Group 2

A.Y. 2024/2025


*Bruno Salvatore*
*Apicella Mario*
*Fiorillo Emanuela*
*Schettini Domenico*
*Engel Alexandre*

# Index

# Introduction

Liver segmentation plays a crucial role in medical imaging, aiding in diagnosis, treatment planning, and disease monitoring. However, segmentation models face challenges due to differences between **Computed Tomography** (CT) and **Magnetic Resonance Imaging** (MRI), known as domain shifts.

**Objective:**

This project focuses on evaluating liver segmentation performance across these two modalities, analyzing model robustness and adaptation strategies.

# Technologies and methods

Pro

OpenCV

augmix

DEEP LEARNING

U-Net

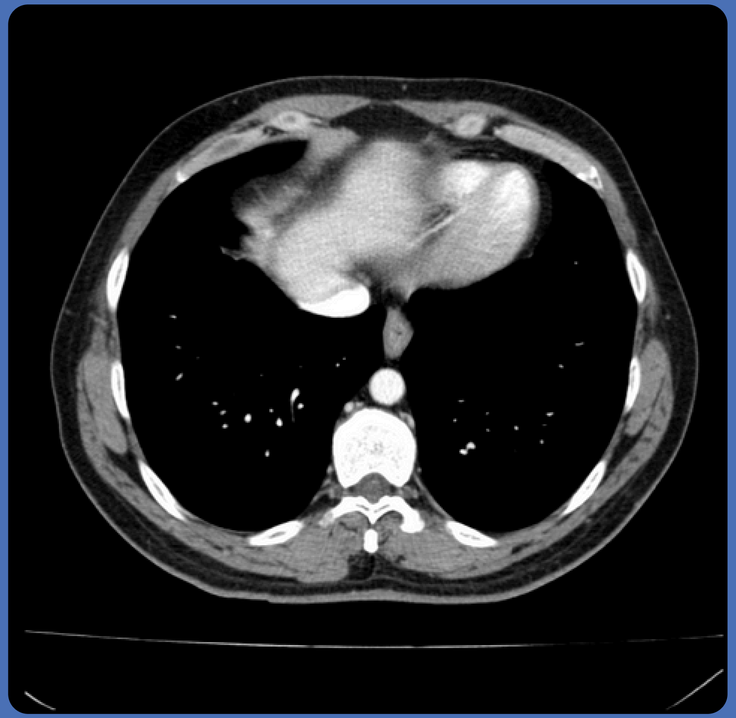
cycleGAN

NVIDIA
A100 GPU

# The CHAOS Dataset: CT

**CT scans use X-rays to generate detailed cross-sectional images, showing high contrast for bones and soft tissues.**

**RAW Images:**



CT Dicom

Mask

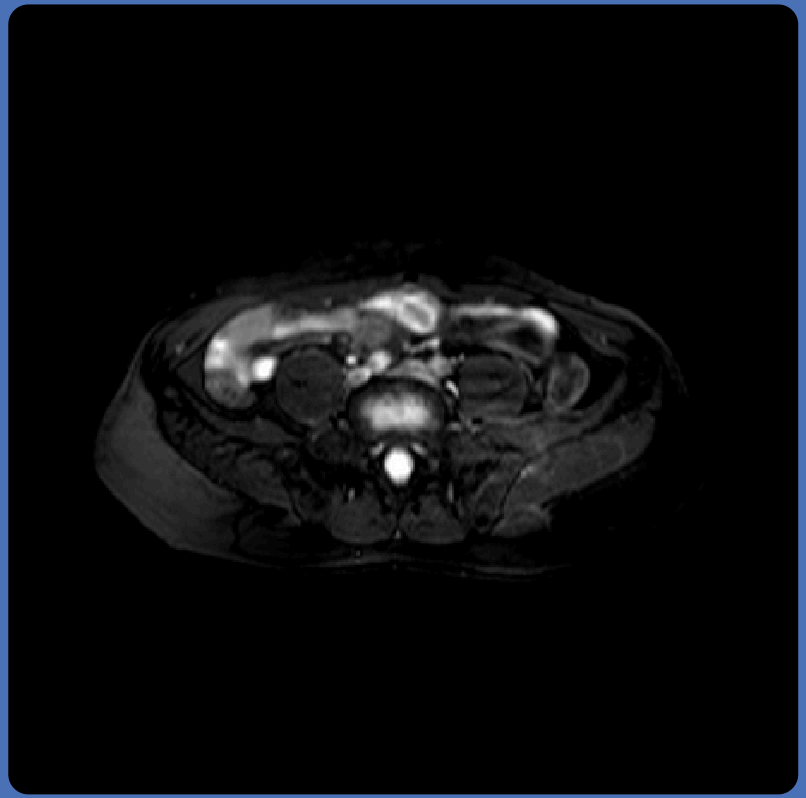
CT masks are already binary, requiring only thresholding for preprocessing

# The CHAOS Dataset: MRI Imaging – T1 vs. T2 Weighted

MRI uses magnetic fields and radio waves to create high-resolution images, with different contrast properties depending on the sequence

RAW Images:

T1DUAL OutPhase



T2SPIR

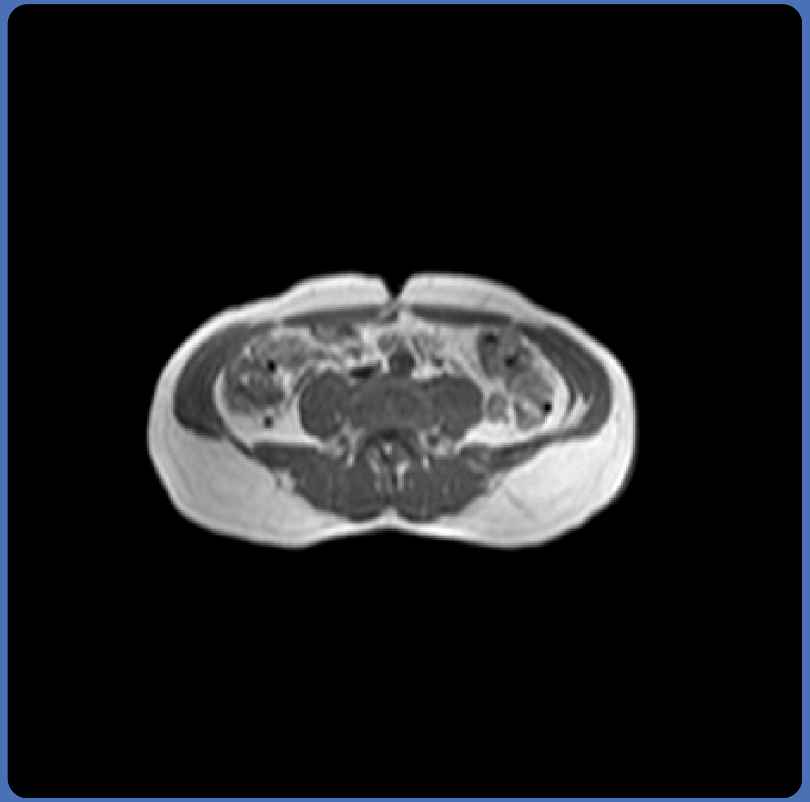
Mask Example

Unlike CT, MRI masks are multiclass, containing multiple anatomical structures such as the liver, kidneys, spleen, and blood vessels
For MRI, we need to extract only the liver mask, requiring additional processing.

# The CHAOS Dataset: T1DUAL, In-Phase vs. Out-Phase

**These sequences highlight fat-water interactions, useful for identifying tissue composition and distinguishing lesions.**

**RAW Images:**



**T1DUAL InPhase**

**T1DUAL OutPhase**

# Pipeline Overview

**To ensure robust liver segmentation across CT and MRI, we follow a structured training pipeline.**

01

Train the model on one domain (CT or MRI) without domain augmentation.

02

Test the model on the opposite domain (MRI or CT) without data augmentation.

03

Train the same model on the initial domain using data augmentation and domain transformation.

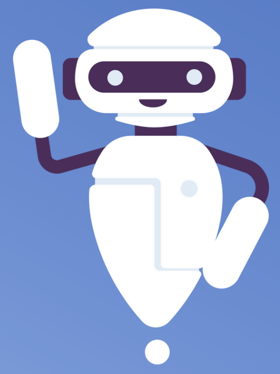
04

Test the augmented model on the second domain to evaluate the effectiveness of trasformations.

# Preprocessing

**Preprocessing ensures that raw medical images are standardized, improving segmentation accuracy and cross-modality generalization.**

## Objectives



### CT Processing:

Intensity standardization, windowing, normalization.

### MRI Processing:

Intensity normalization, T1/T2 handling, mask selection.

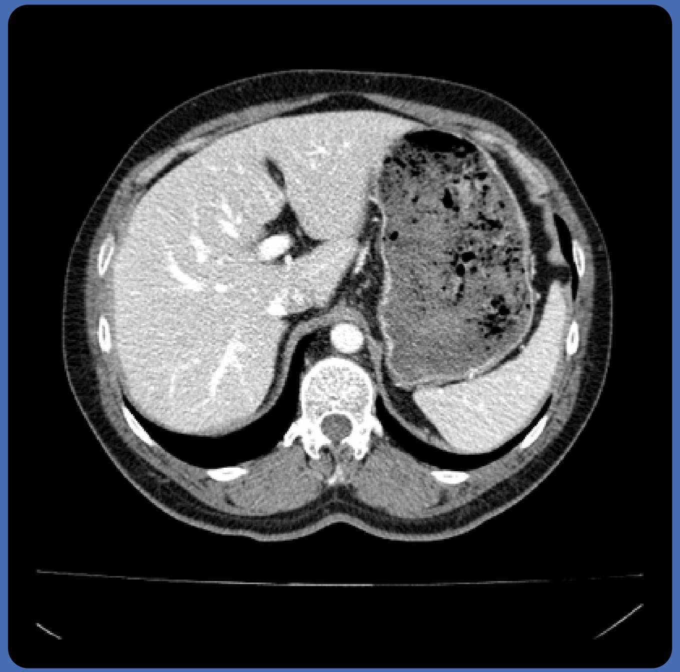
### Mask Processing:

Binarization for uniform segmentation labels.

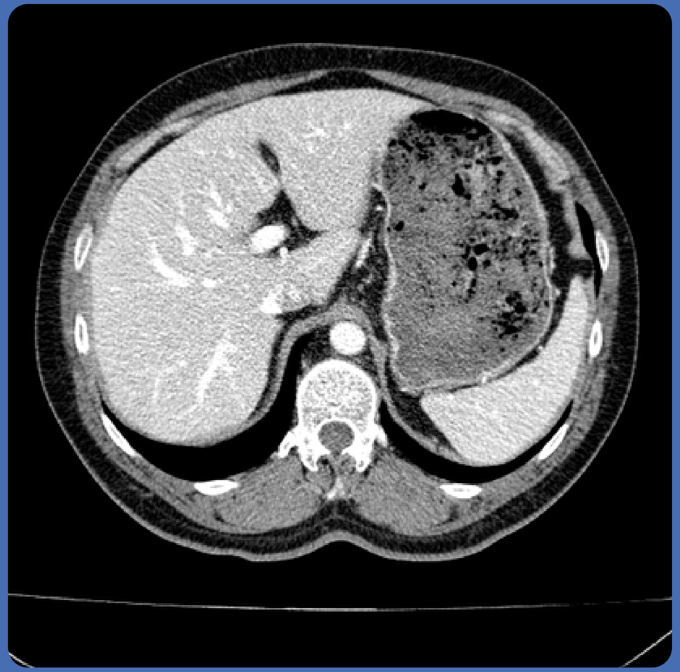
# Preprocessing: CT Images

CT images are standardized using intensity correction and windowing to enhance relevant structures

1. Rescale Slope & Intercept (Hounsfield Units Conversion).
2. Windowing (adaptive contrast) using WC (Window Center) and WW (Window Width).
3. Normalization (0-1 scaling) to uniform the intensity



DICOM file



Post-Preprocessing

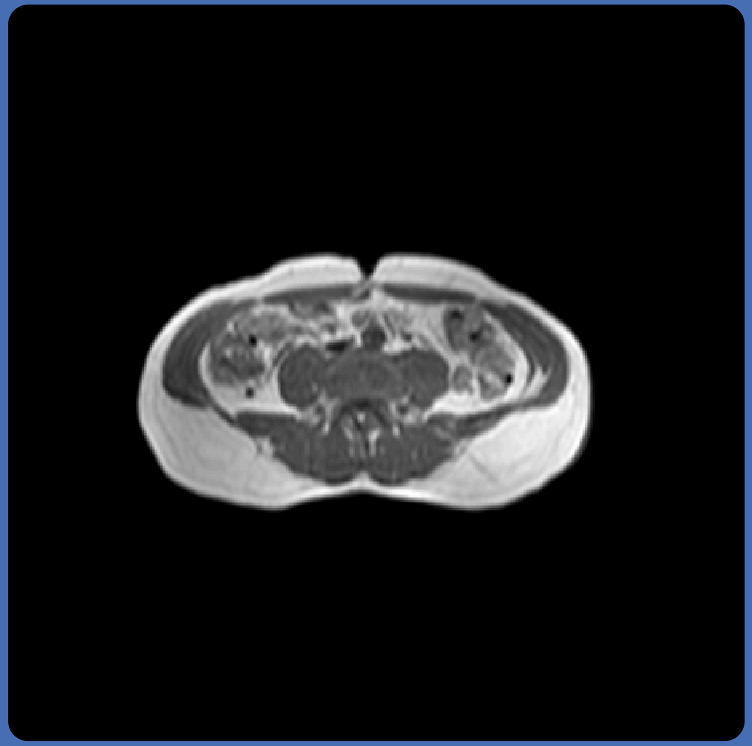
Windowing enhances liver structures while reducing noise.

# Preprocessing: MRI Images

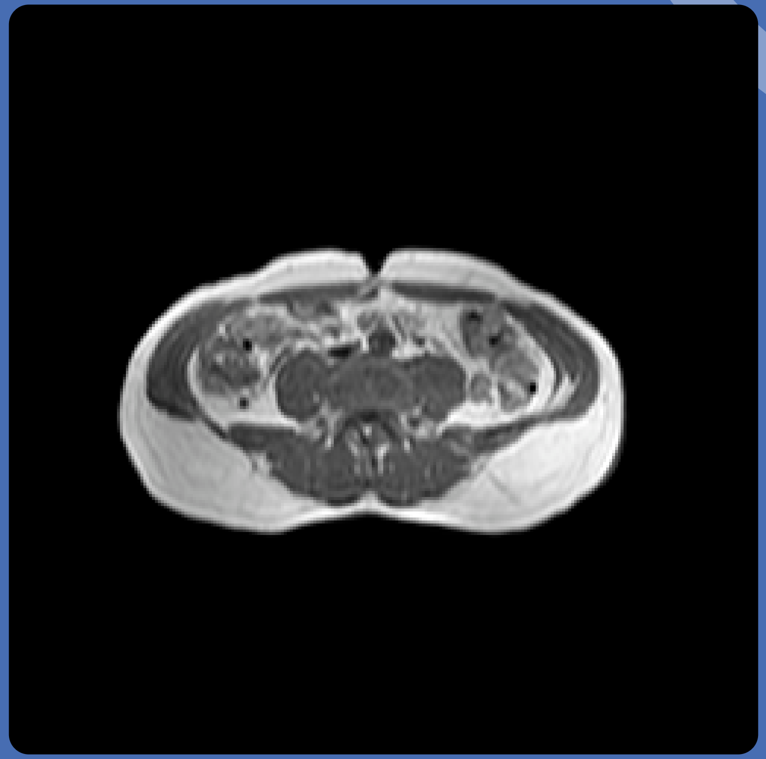
**MRI images have no fixed intensity scale, requiring additional standardization**

**Standardized intensity distribution improves segmentation performance.**

1. Rescale Slope & Intercept (Hounsfield Units Conversion).
2. Windowing (adaptive contrast) using WC (Window Center) and WW (Window Width).
3. Normalization (0-1 scaling) to uniform the intensity



DICOM file



Post-Preprocessing

# Preprocessing: MRI Images

**MRI images have no fixed intensity scale, requiring additional standardization**

MRI Multiclass Mask

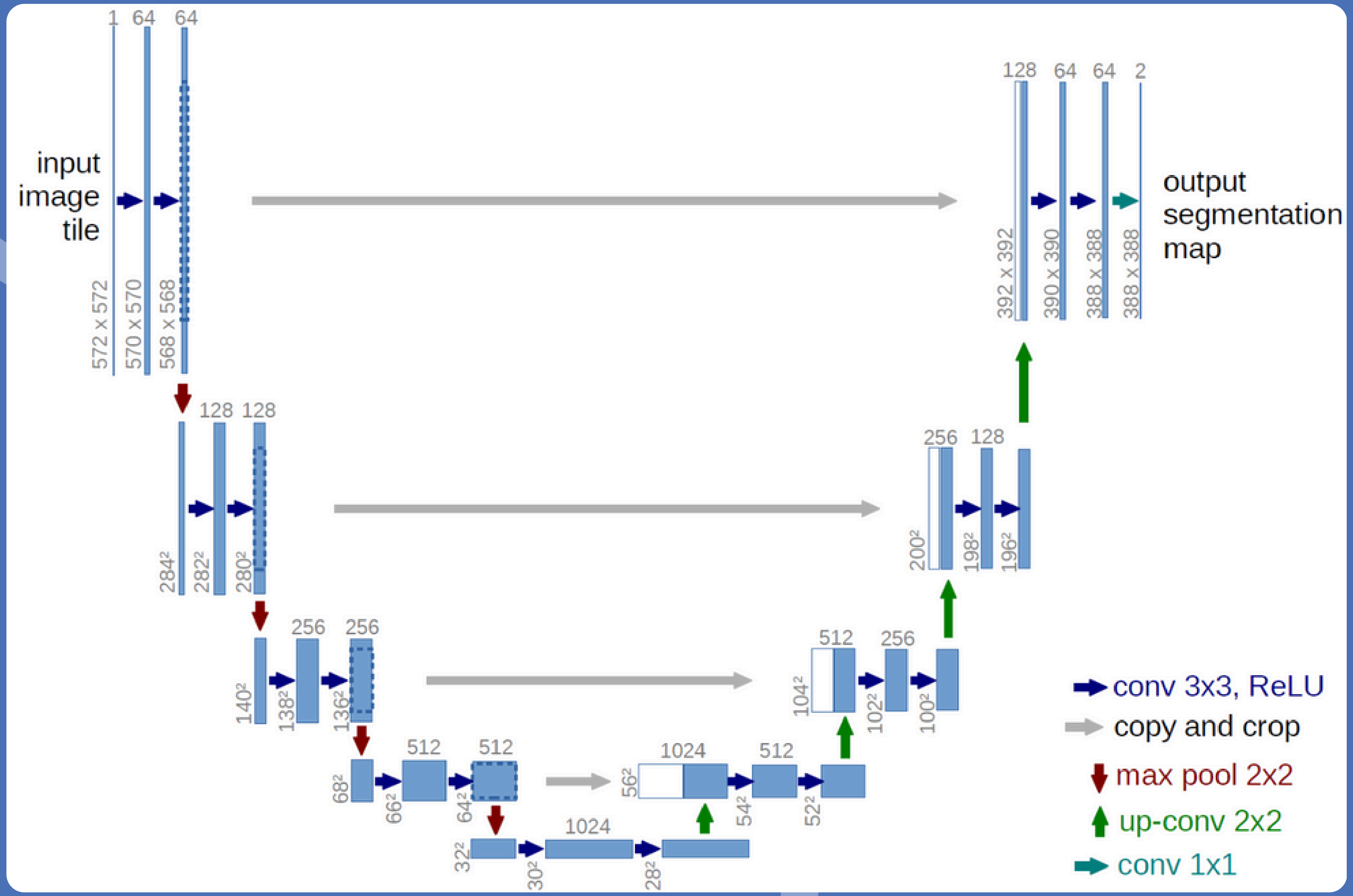
Preprocessed Mask

1. CT Mask Binarization: Thresholding with fixed value (>127).
2. Since MRI masks are multi-class, only the liver mask is selected. The liver region was identified within a grayscale intensity range
3. Final conversion to binary (0/1).

# Baseline Training – Objective & Setup

**Before applying augmentation, we first evaluate the model's performance when trained only on one modality (CT or MRI)**

- Why is this step important?
- ✅ Understand how well the model performs within the same domain.
- ✅ Identify potential performance degradation due to domain shift when tested on a different modality




Optimizer: Adam
Learning Rate: 0.001

## Training Setup:

- Model: U-Net (It was choosen the 2D one).

## Training Data:

- CT-only training → CT test ✅ (Expected good performance).
- MRI-only training → MRI test ✅ (Expected good performance).
- CT-trained model → MRI test ❌ (Expected domain shift issue).
- MRI-trained model → CTtest ❌ (Expected domain shift issue).

## Loss Functions:

- Dice Loss (for segmentation accuracy).
- Binary Cross-Entropy (BCE) (to handle class imbalance).
- Jaccard Loss (for additional segmentation evaluation).

This experiment sets the baseline to compare with domain adaptation techniques.

# Training Process & Domain Shift Effect

TABLE I
PERFORMANCE METRICS FOR MRI → MRI

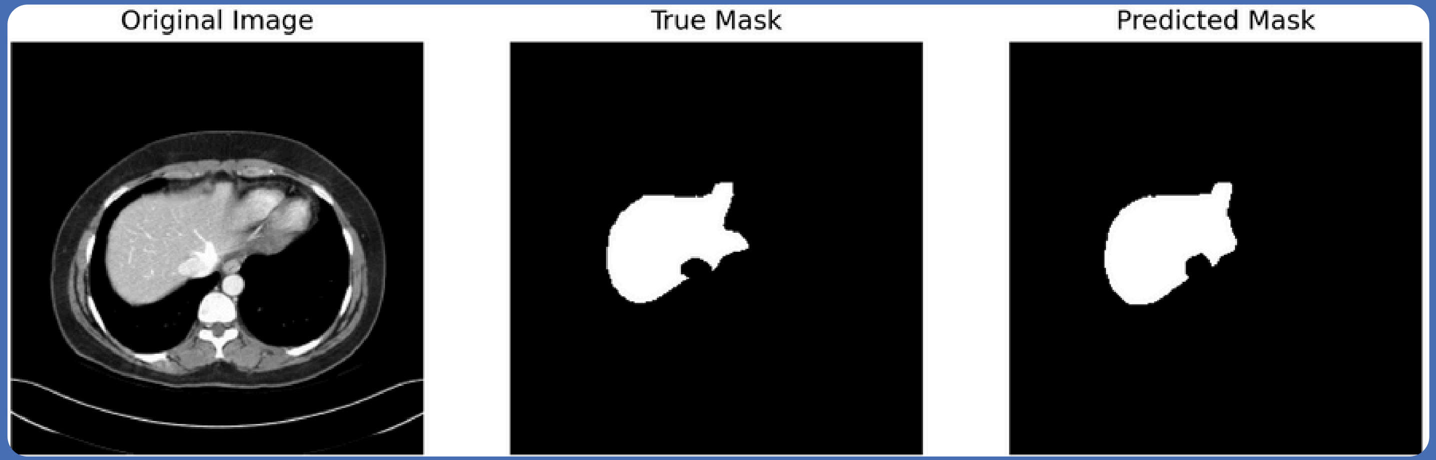
| Metric | Value |
|---|---|
| Dice Score | 0.8929 |
| BCE Loss | 0.0173 |
| Dice Loss | 0.1071 |
| Jaccard Loss | 0.1927 |
| Total Loss | 0.0979 |

TABLE II
PERFORMANCE METRICS FOR CT → CT

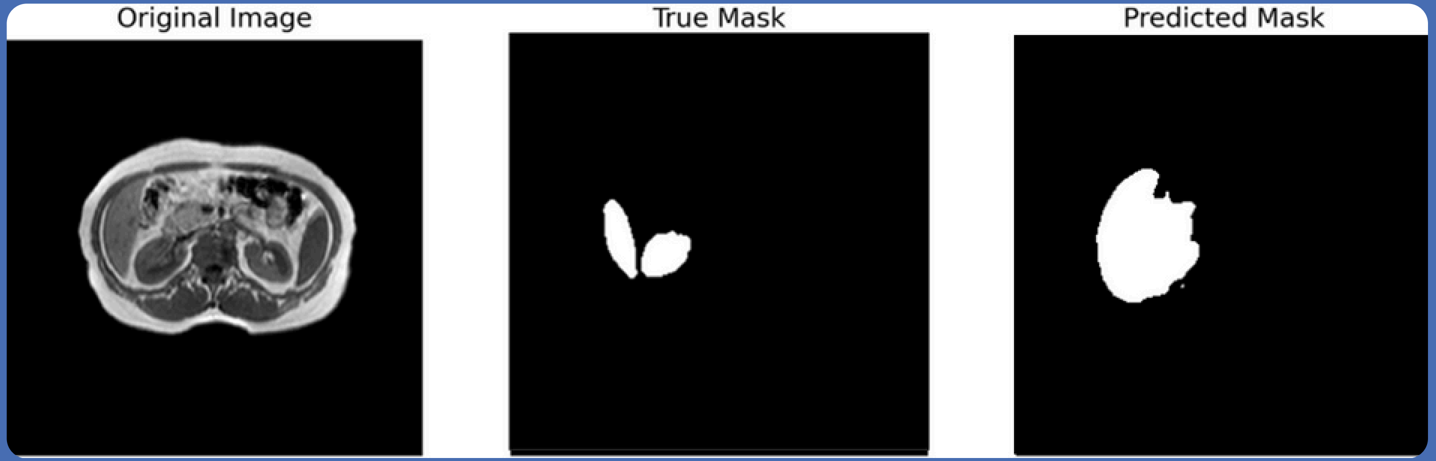
| Metric | Value |
|---|---|
| Dice Score | 0.9242 |
| BCE Loss | 0.0845 |
| Dice Loss | 0.0827 |
| Jaccard Loss | 0.1508 |
| Total Loss | 0.0889 |

**The results show high segmentation accuracy when trained and tested on the same domain.**

**CT → CT**




**MR → MR**




# Training Process & Domain Shift Effect

When tested on a different domain, performance drops drastically, confirming the presence of a severe domain shift between CT and MRI.

TABLE III
PERFORMANCE METRICS FOR CT → MRI

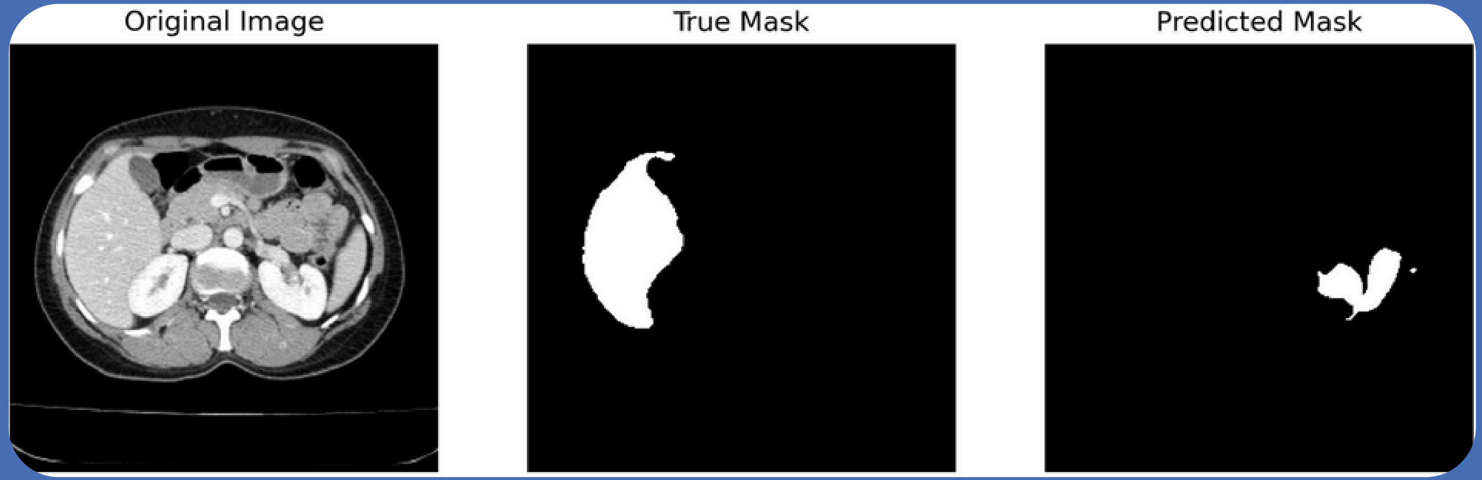
| Metric | Value |
|---|---|
| Dice Score | 0.0097 |
| BCE Loss | 0.6166 |
| Dice Loss | 0.9897 |
| Jaccard Loss | 0.9948 |
| Total Loss | 0.8675 |

TABLE IV
PERFORMANCE METRICS FOR MRI → CT

| Metric | Value |
|---|---|
| Dice Score | 0.00015 |
| BCE Loss | 0.6863 |
| Dice Loss | 0.9998 |
| Jaccard Loss | 0.9999 |
| Total Loss | 0.9067 |

CT → MR

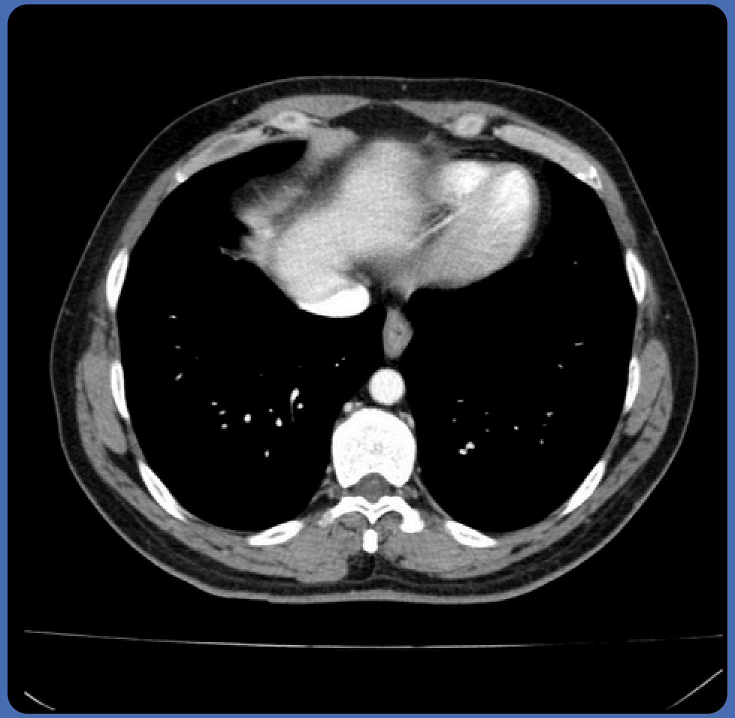

MR → CT




# Why Do We Need Data Augmentation?

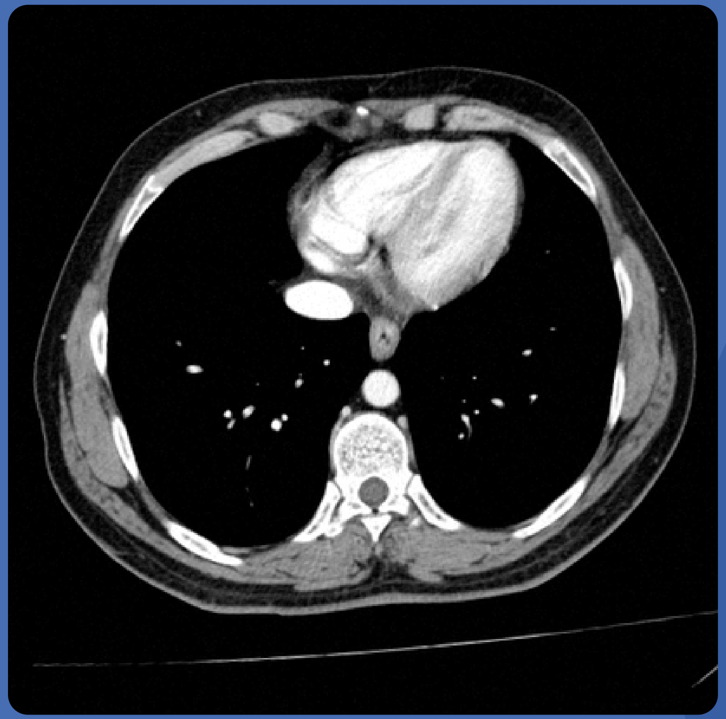
✅ "Medical images are limited in quantity and vary significantly across modalities (CT vs. MRI)."
✅ "Augmentation improves generalization by increasing diversity in the dataset."

- Domain Adaptation (CT → MRI, MRI → CT)
- AugMix (Photometric & Geometric Transformations on Raw Images)



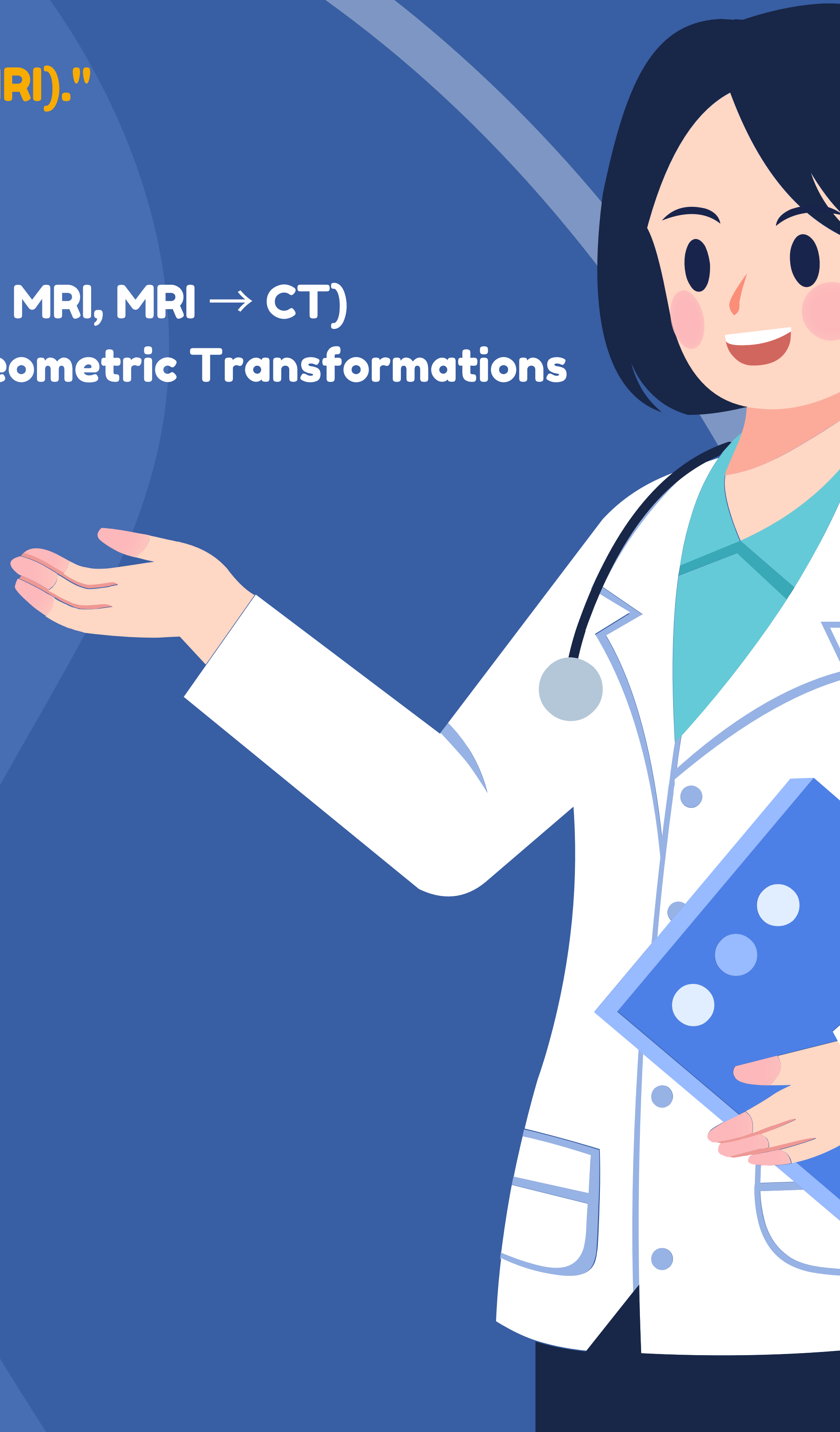
Preprocessed Image

Augmented Image



Transformed Image

The images show augmented images on CT domain but the same procedures have been made on MRI



# First Augumentation - Domain Transformation

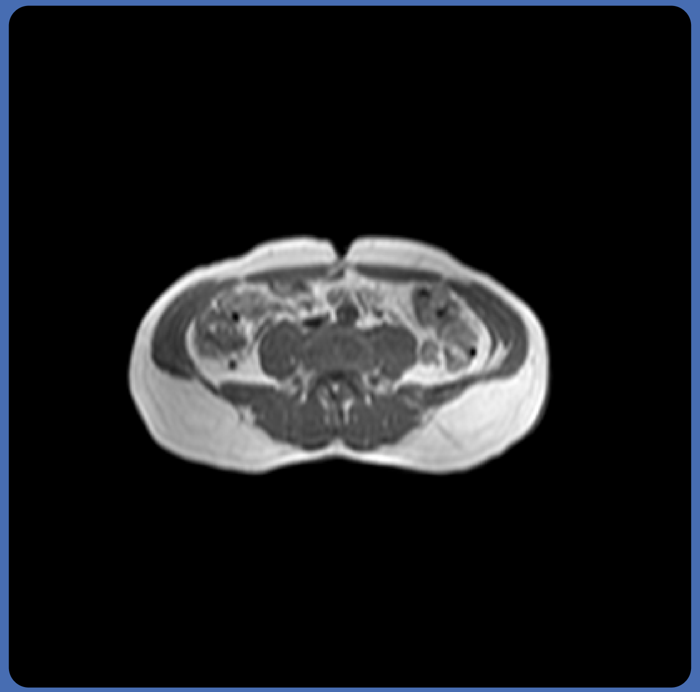
CT and MRI have different contrast and intensity distributions.
To bridge the gap, we transform CT scans to look like MRI and vice versa.

## How It Works:

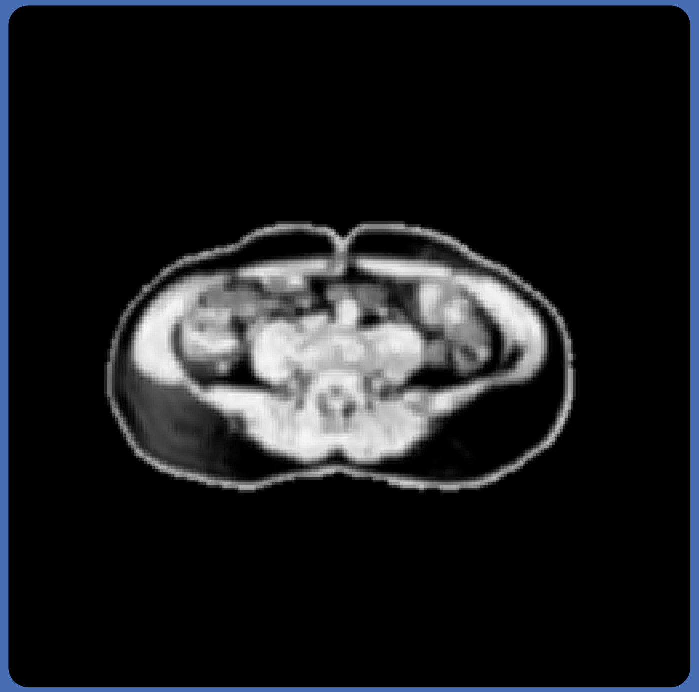
- CT is converted into T1-weighted MRI or T2-weighted MRI
- MRI (T1/T2) is modified to resemble CT attenuation properties

### Transformations Applied:

- ✅ Edge Detection & Distance Map Calculation
- ✅ Tissue Masking (CSF, Fat, Muscle, Bone, etc.)
- ✅ Contrast and Brightness Adjustments
- ✅ Filtering and Histogram Equalization



T1DUAL InPhase

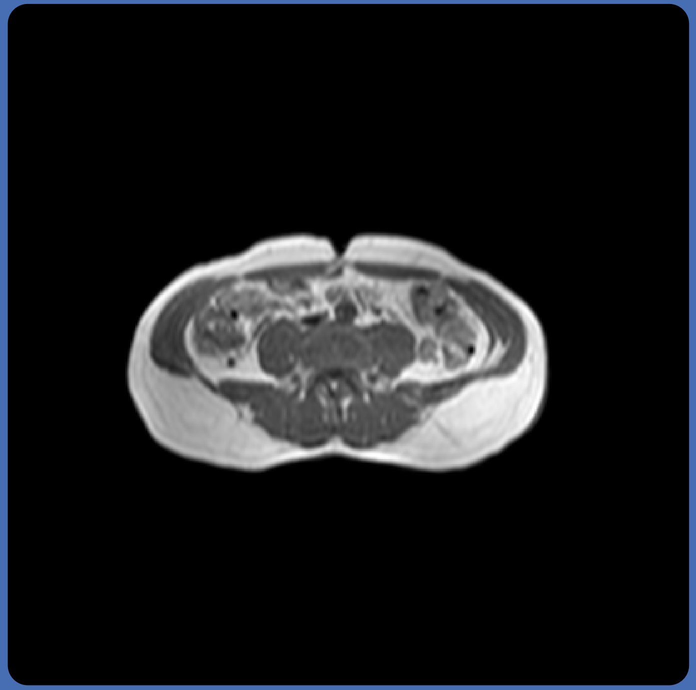


InPhase Augmented

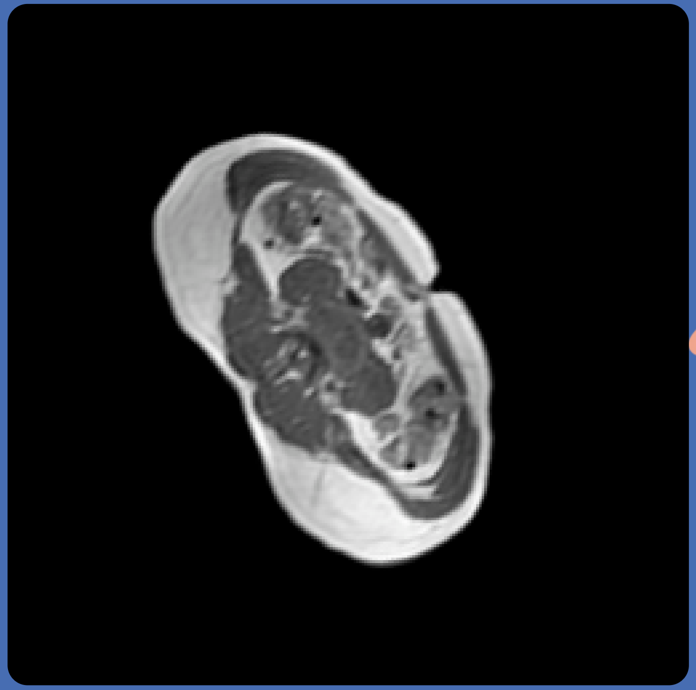
# Second Augumentation - AugMix Approach

**Medical images must be robust to noise, lighting changes, and geometric distortions.  AugMix generates new variations while preserving structure.**

- Types of Augmentations Applied:
- ✅ Noise Transformations (Salt-and-Pepper noise, Gaussian Blur, Median Blur, Bilateral Filter)
- ✅ Photometric Transformations (Brightness, Contrast, Sharpness Adjustments, Gamma Correction)
- ✅ Geometric Transformations (Rotation, Translation, Flipping)
- ✅ Histogram Equalization with CLAHE (Enhancing contrast adaptively)



T1DUAL InPhase



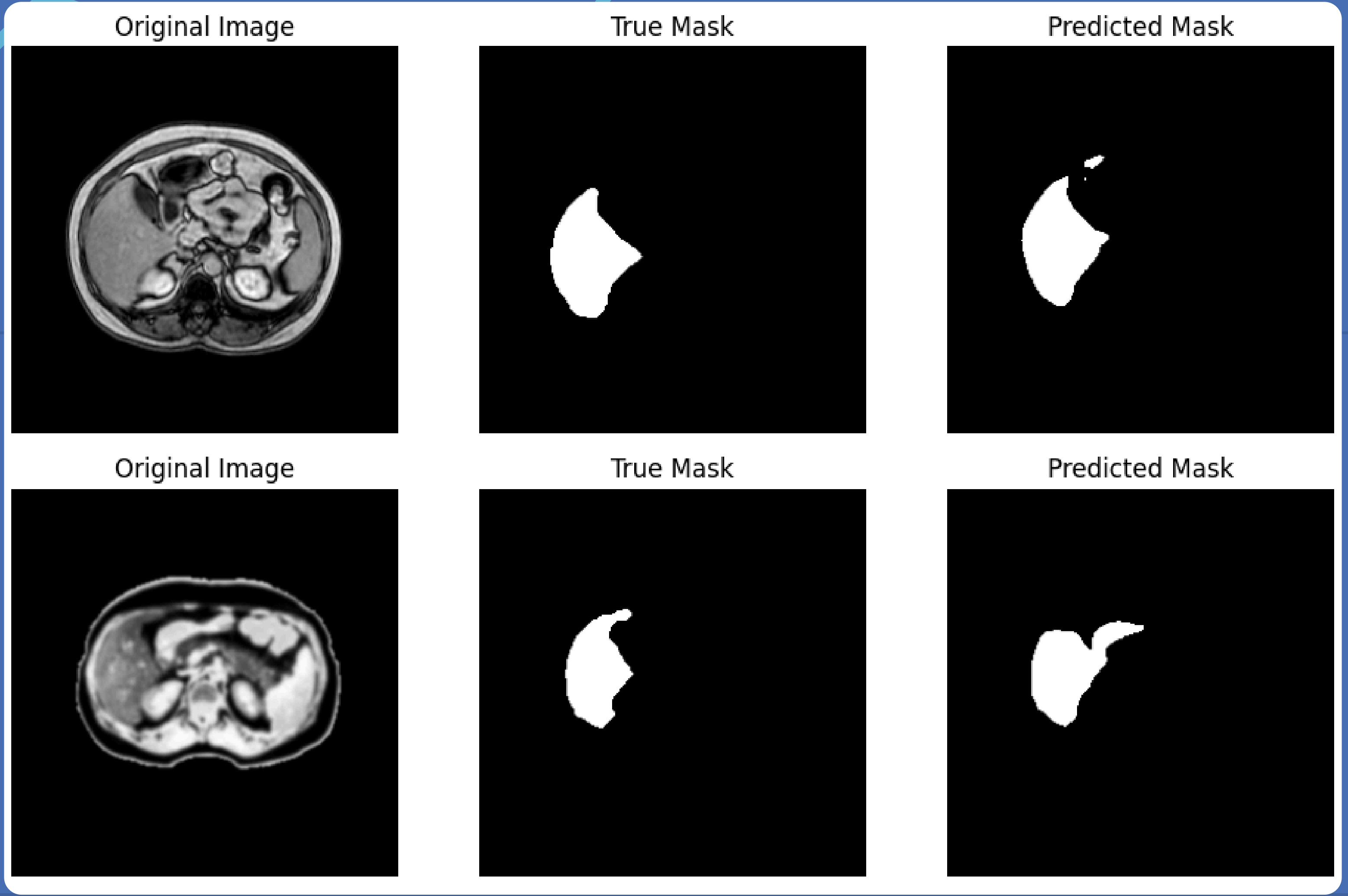
InPhase Augmix

# Training Process & Domain Shift Effect

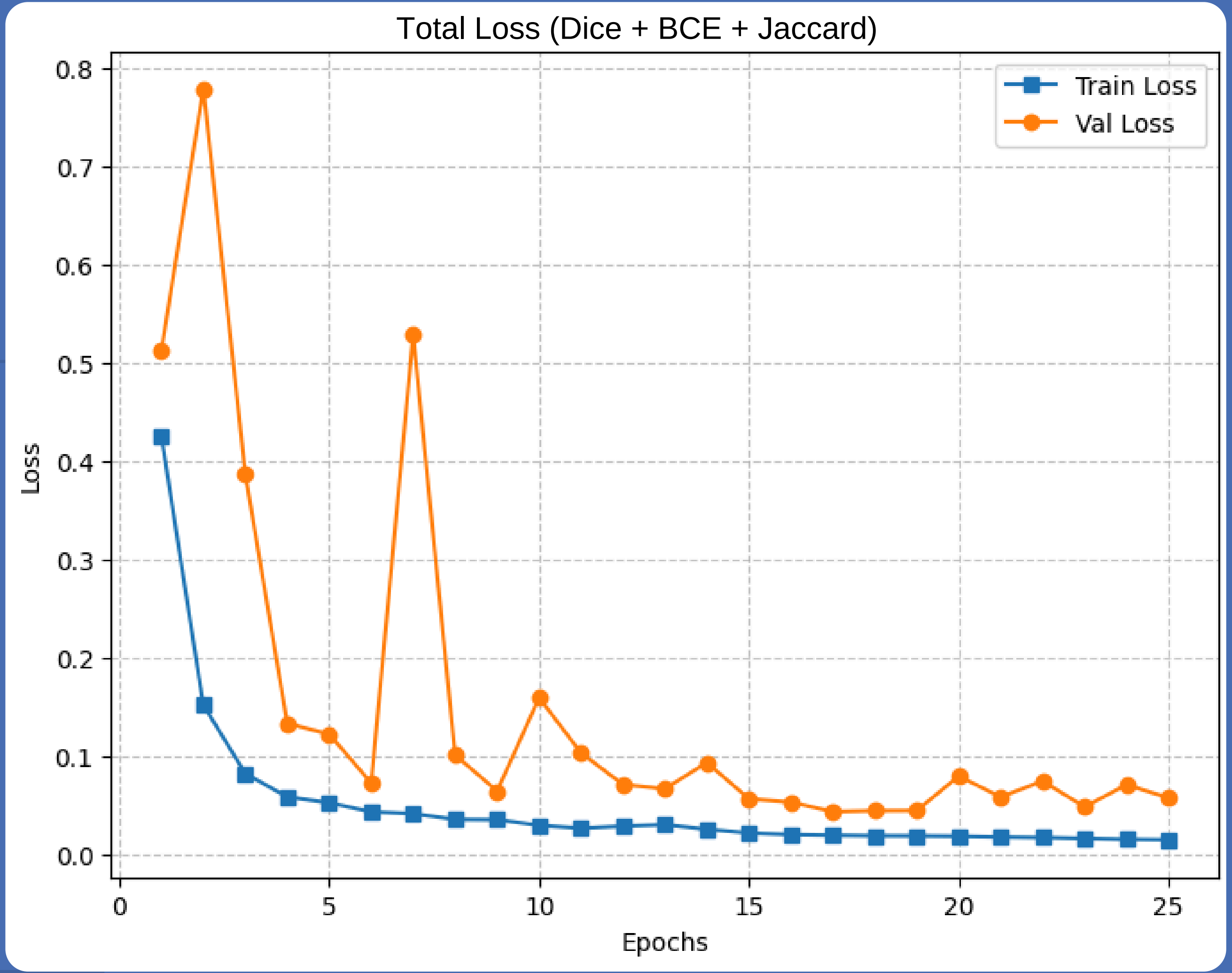
TABLE V
PERFORMANCE METRICS FOR CROSS-DOMAIN TESTING

| Evaluation | Dice Score | Loss |
|---|---|---|
| CT $\rightarrow$ MRI | 0.3419 | 0.6581 |
| MRI $\rightarrow$ CT | 0.7502 | 0.2514 |

CT model




Comparison true Mask and Predicted




Total Loss (Dice - BCE -Jaccard)

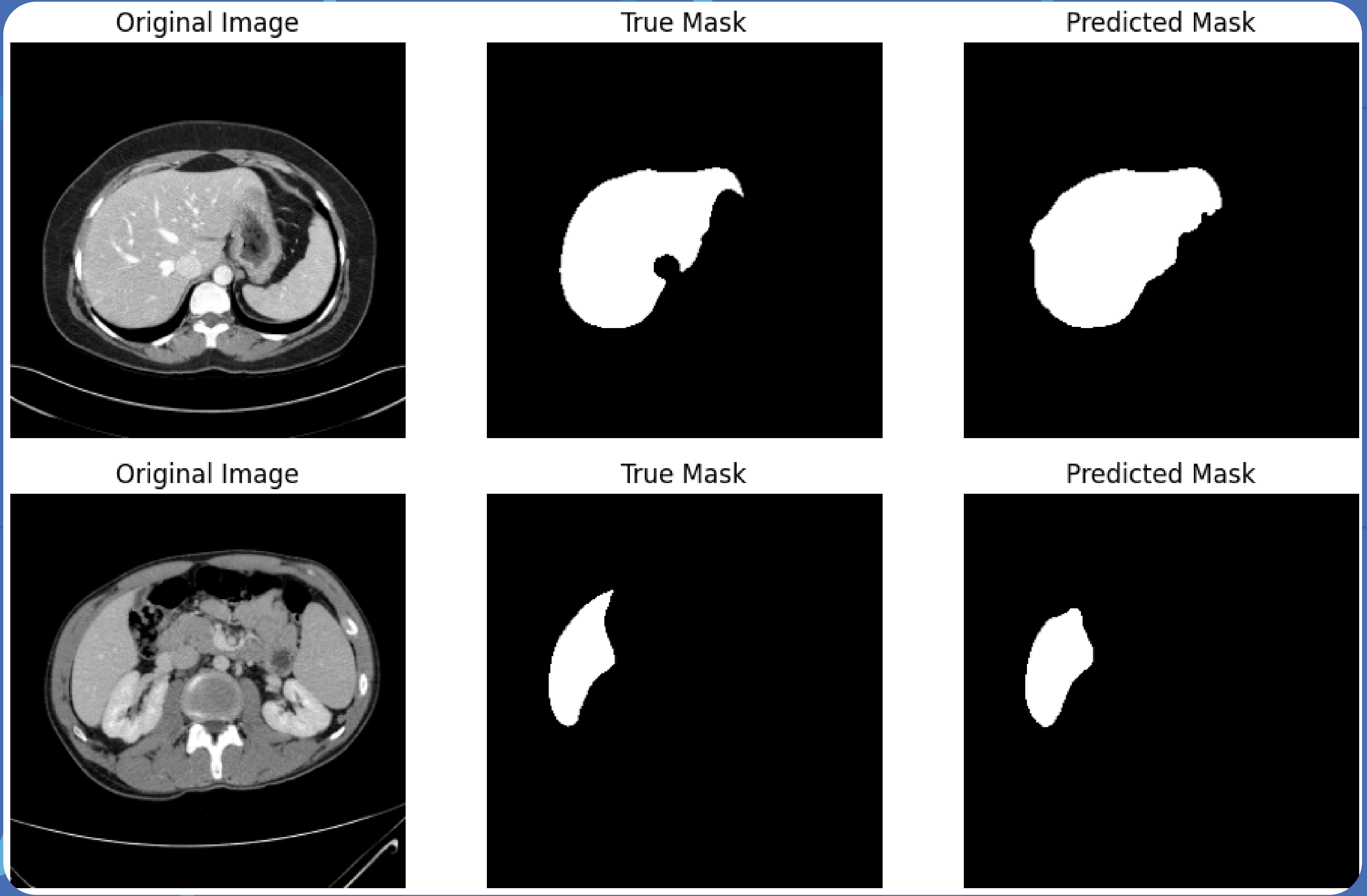
# Training Process & Domain Shift Effect

**MR model**

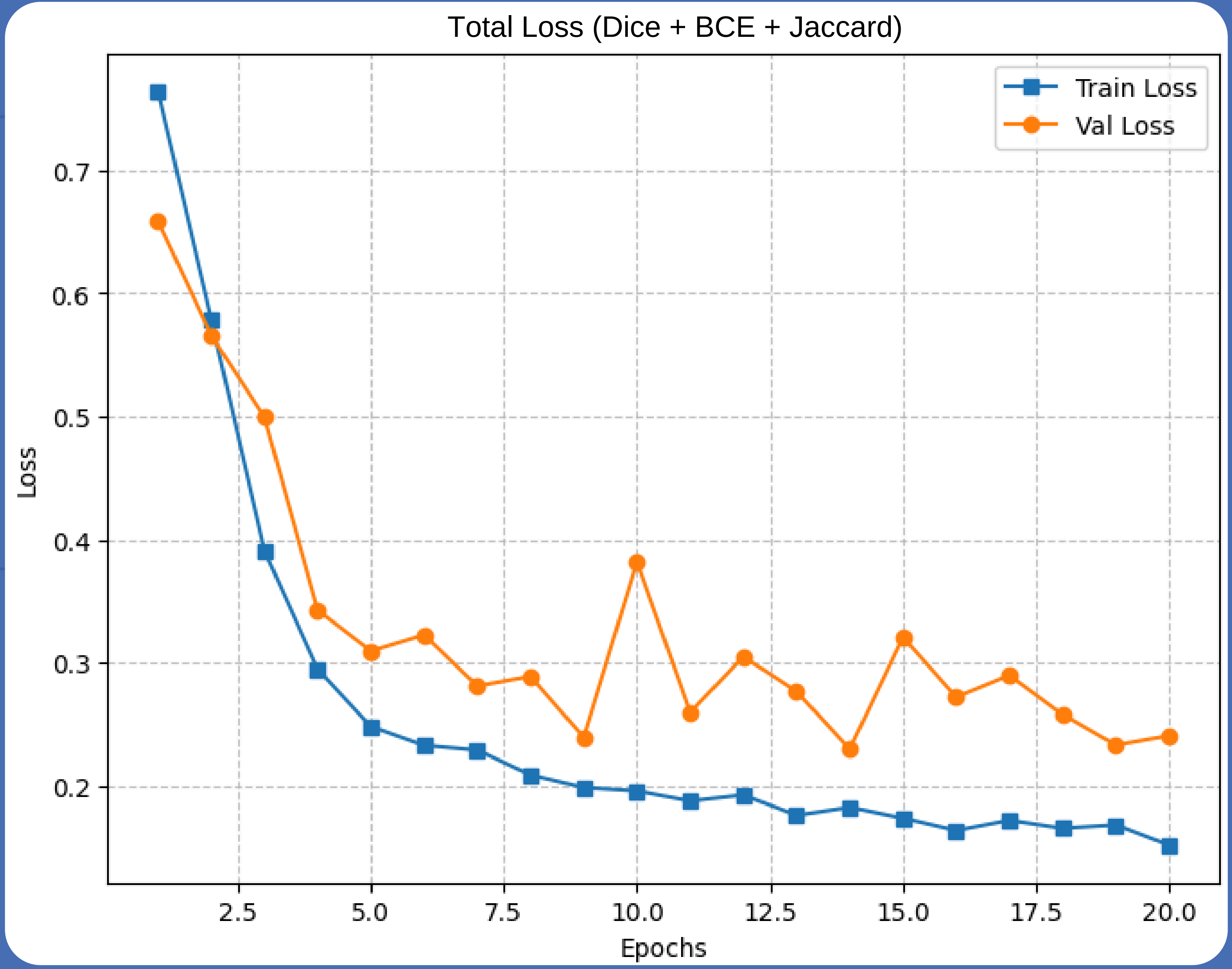
TABLE V

PERFORMANCE METRICS FOR CROSS-DOMAIN TESTING

| Evaluation | Dice Score | Loss |
|---|---|---|
| CT → MRI | 0.3419 | 0.6581 |
| MRI → CT | 0.7502 | 0.2514 |



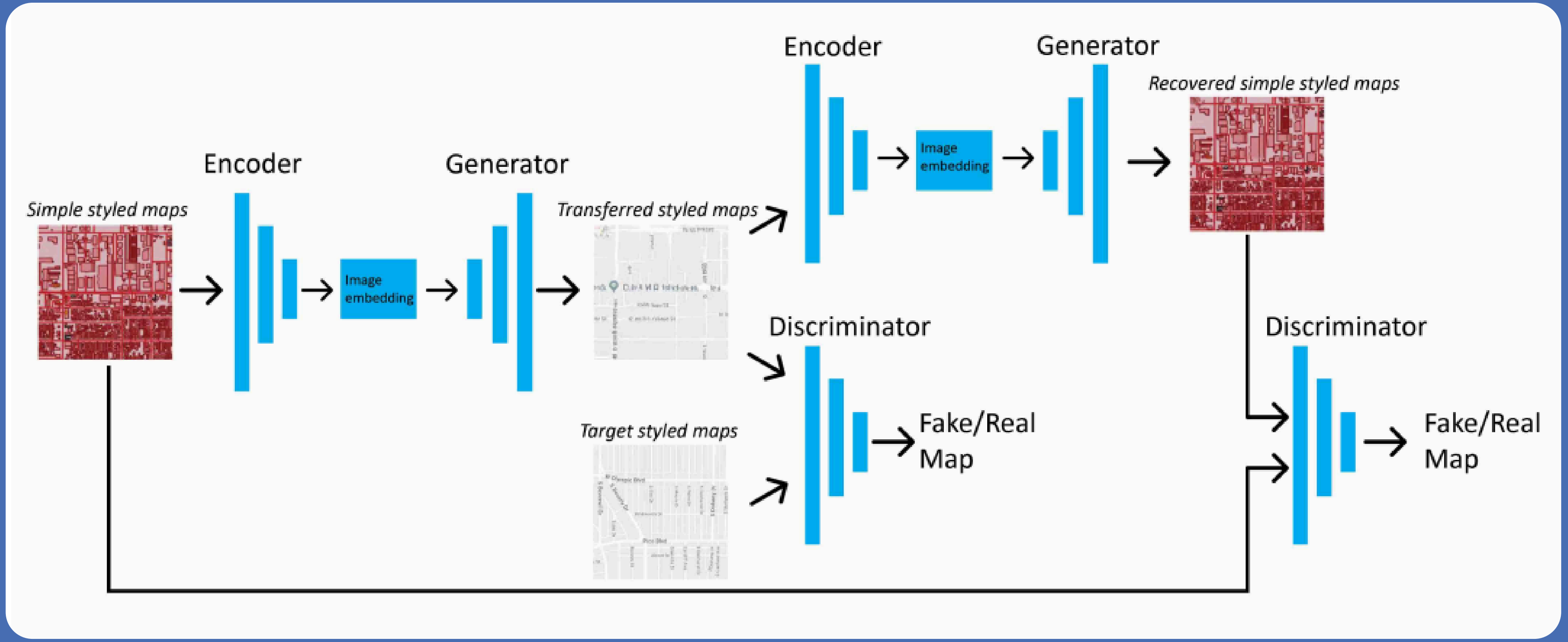

**Comparison true Mask and Predicted**

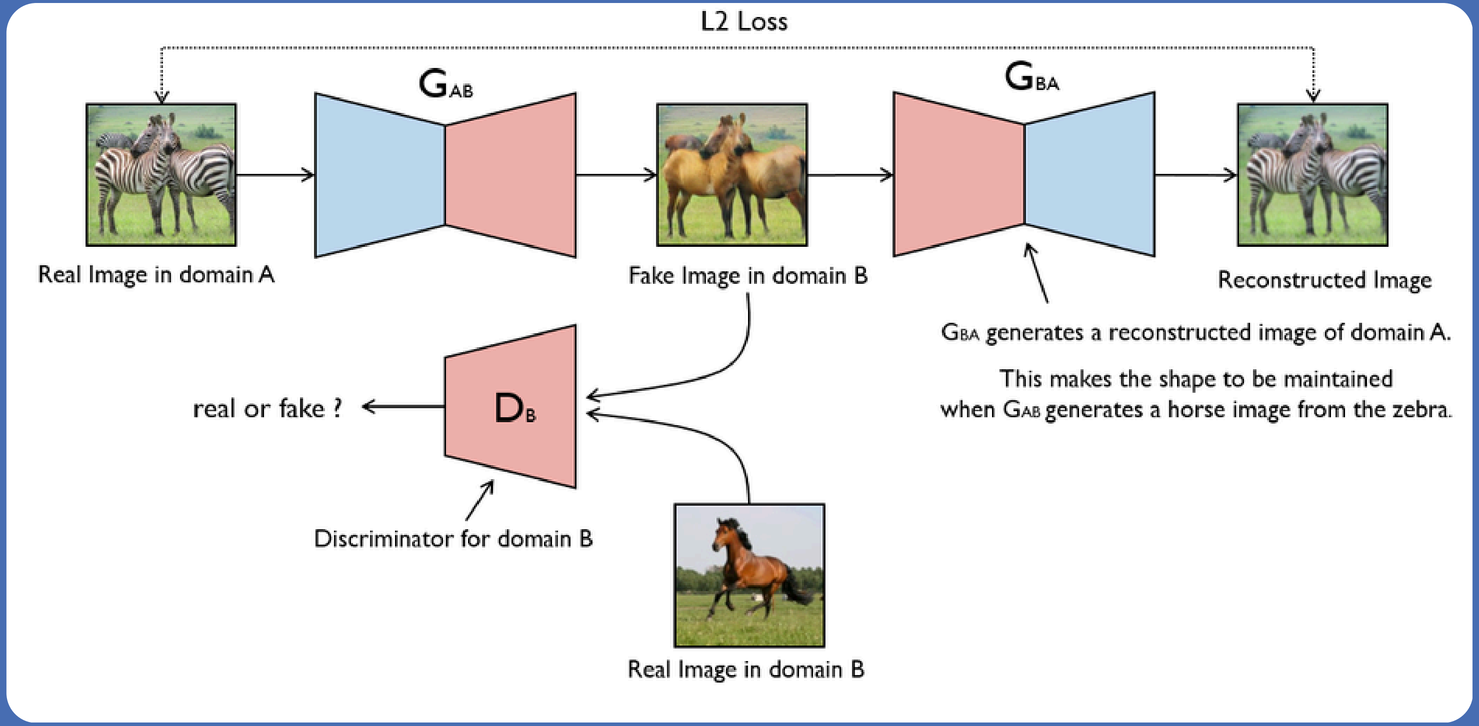



**Total Loss (Dice - BCE -Jaccard)**

# CycleGAN for Domain Adaptation (Comparison Study)

To evaluate the effectiveness of our augmentation approach, we trained an additional model using CycleGAN for domain adaptation. This CycleGAN-based model is used as a comparison to the AugMix-augmented model, but it is NOT part of the final pipeline.




CycleGAN is a generative adversarial network (GAN) that learns to transform images between two domains (CT ⇄ MRI) without paired data.  It allows CT scans to be translated into an MRI-like style and vice versa."

# Training CycleGAN for CT ⇄ MRI Transformation

**First of all, the Model has been trained.**

01

### Dataset & Preprocessing:

CT & MRI Images
Pairing Strategy
Ground Truth Masks

02

### CycleGAN Architecture:

Two Generators (G & F)
Two Discriminators (D_A & D_B).

03

### Loss Functions Used:

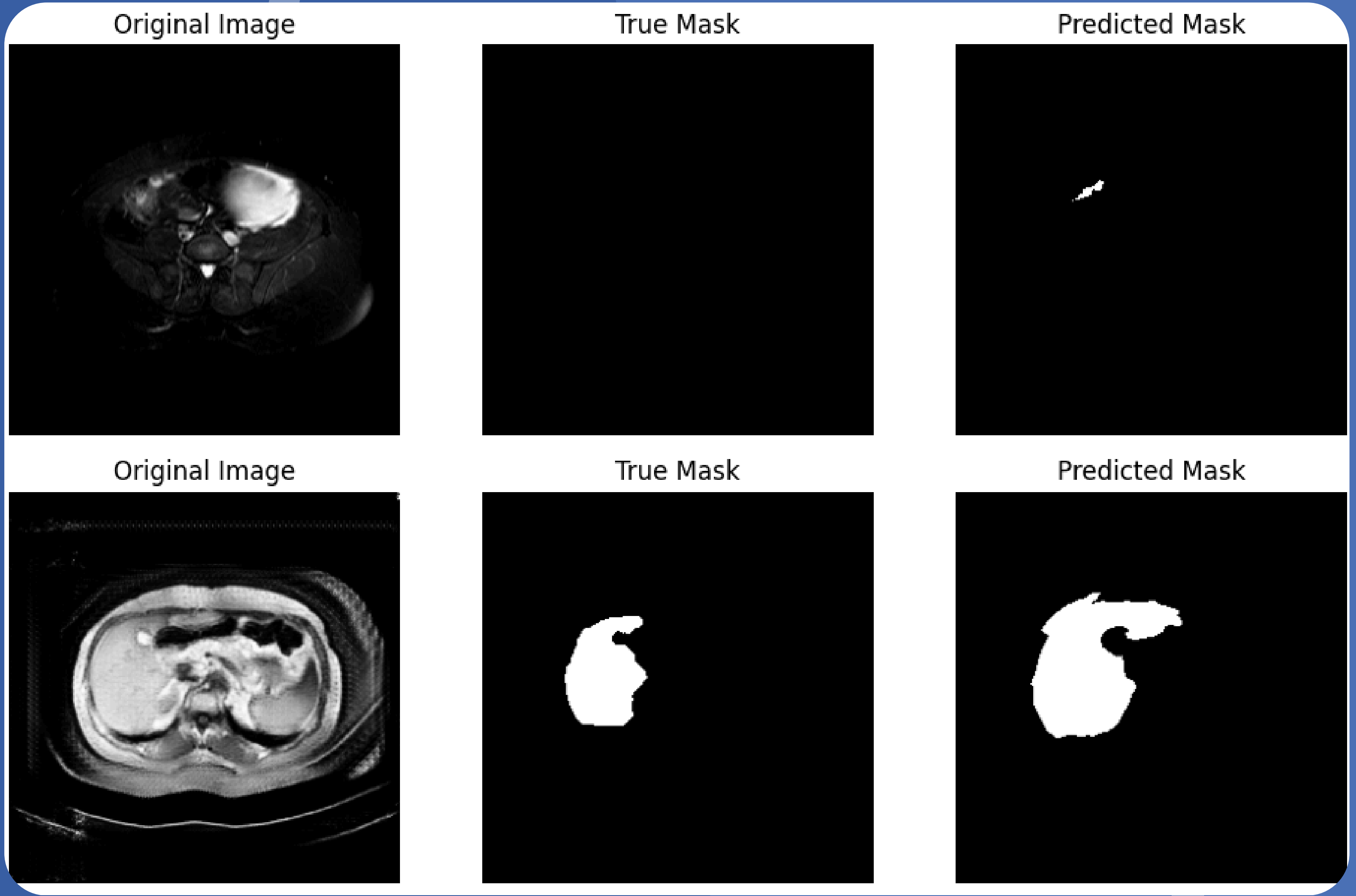
Adversarial Loss (MSE): Ensures realistic CT ⇄ MRI translation.
Cycle Consistency Loss (L1): Preserves structural integrity by enforcing reversibility.
Identity Loss (L1): Maintains color and contrast fidelity.

# CycleGAN Results

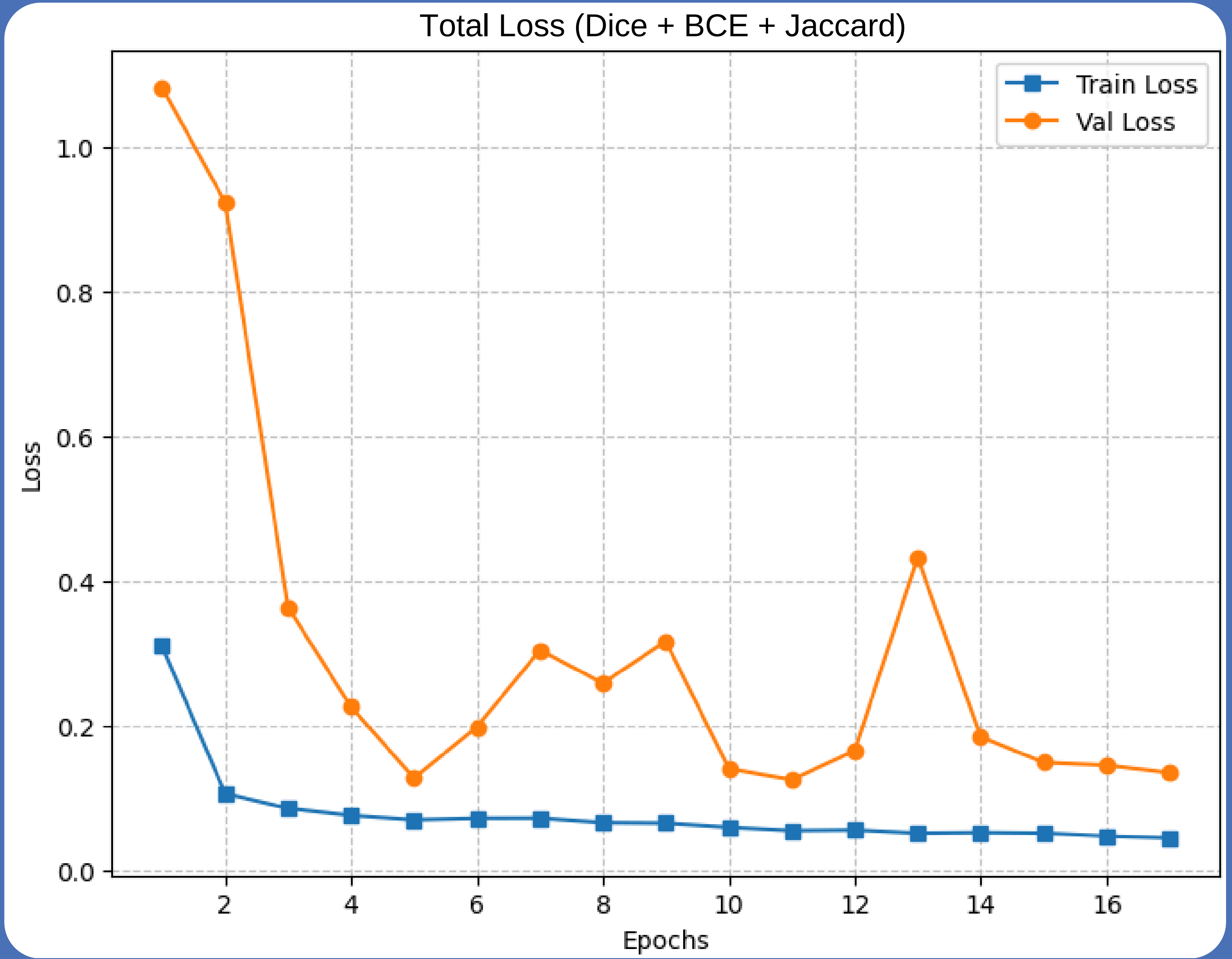
TABLE VI
CYCLEGAN-BASED U-NET EVALUATION RESULTS

| Domain | Dice Score | Loss |
|---|---|---|
| CT → MR | 0.1904 | 0.8077 |
| MR → CT | 0.1378 | 0.9911 |

**CT model**




**Comparison true Mask and Predicted**



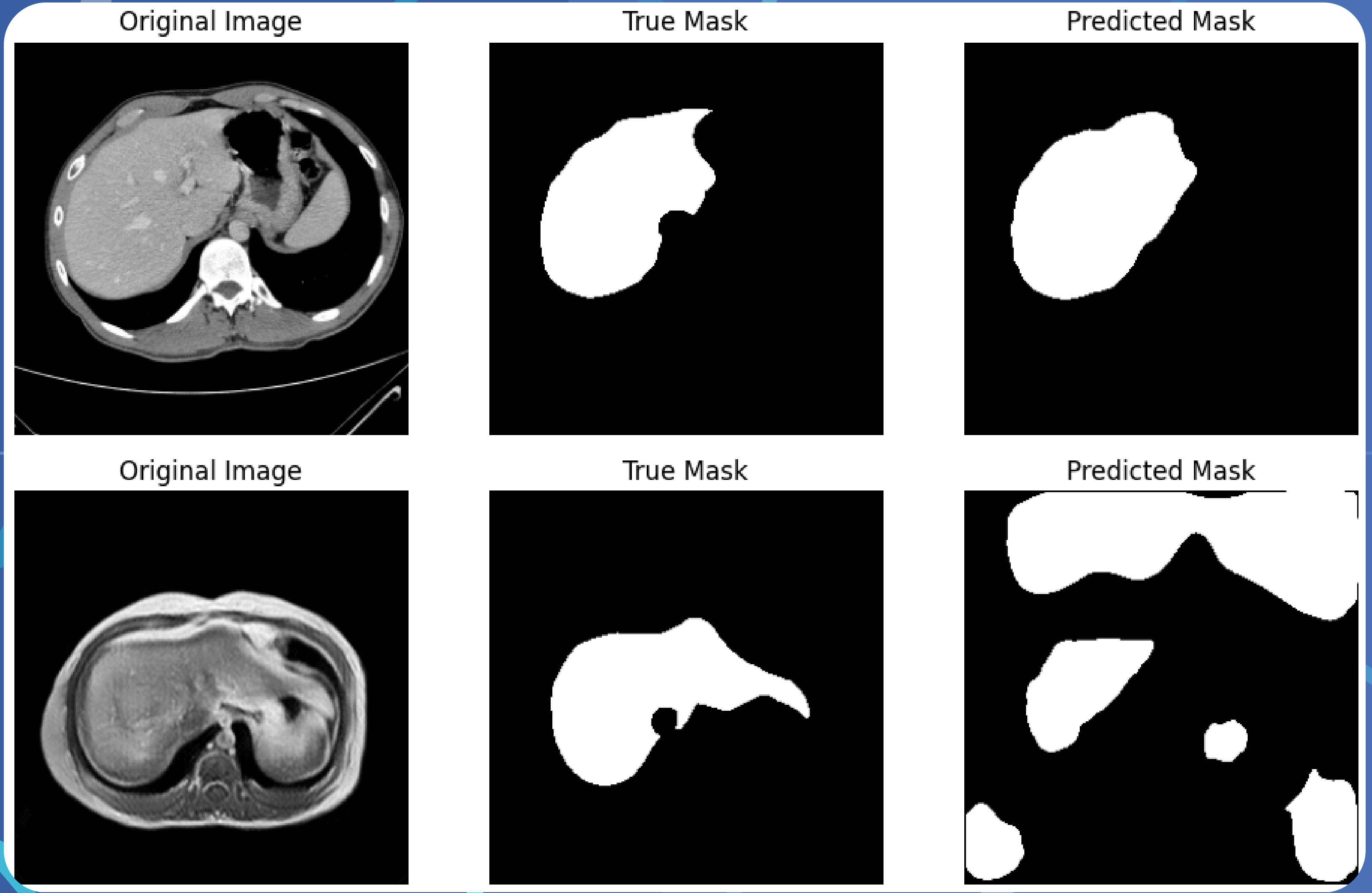

**Total Loss (Dice - BCE -Jaccard)**

# CycleGAN Results

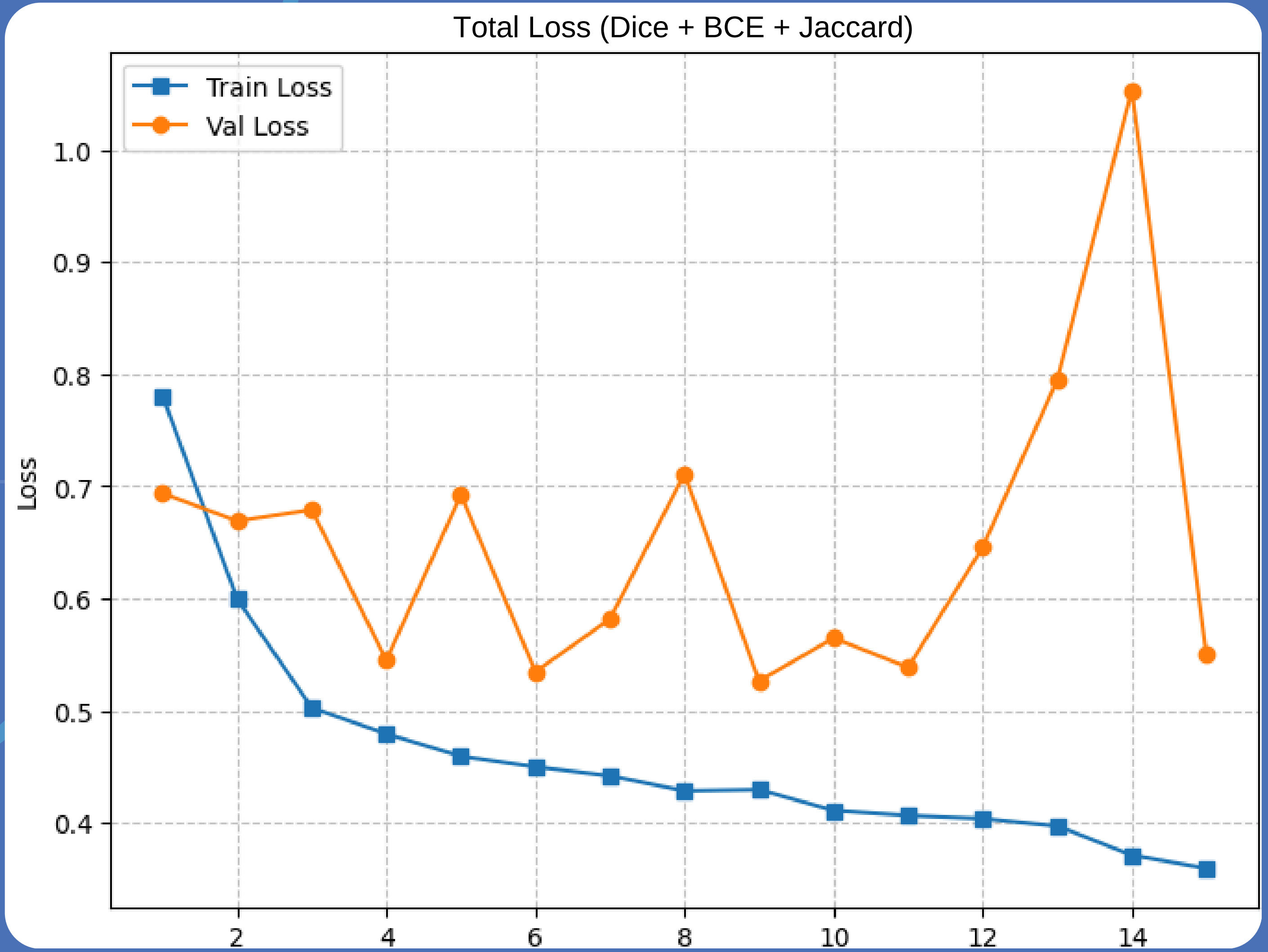
**MR model**

TABLE VI
CYCLEGAN-BASED U-NET EVALUATION RESULTS

| Domain | Dice Score | Loss |
|---|---|---|
| CT → MR | 0.1904 | 0.8077 |
| MR → CT | 0.1378 | 0.9911 |




**Comparison true Mask and Predicted**




**Total Loss (Dice - BCE -Jaccard)**

# Conclusions and Future perspectives

The results presented in these slides demonstrate that on the same domain a model works well, but struggles to generalize across different imaging modalities. AugMix and image augmentations significantly improve cross-domain performance, while CycleGAN-based domain adaptation is less effective.

These findings highlight the importance of structured augmentations in mitigating domain shift, demonstrating that hybrid approaches combining data augmentation and domain translation could further improve segmentation robustness.

Future work could explore:
- Combining CycleGAN and AugMix to enhance domain generalization.
- Incorporating self-supervised learning to leverage unlabeled data.
- Applying multi-scale feature fusion to improve anatomical consistency across modalities.

# THANK YOU