MRI Scan T1-T2 Image Style Transfer Using CycleGAN

Abstract

Magnetic Resonance Imaging (MRI) is a cornerstone of modern diagnostic radiology, offering multiple modalities such as T1-weighted and T2-weighted scans. However, acquiring both modalities for every patient can be time-consuming and costly. This study explores the use of Cycle-Consistent Generative Adversarial Networks (CycleGANs) to perform style transfer between T1 and T2 MRI images. By training a deep learning model on paired datasets, we demonstrate the feasibility of generating realistic T2 images from T1 inputs and vice versa. The model architecture leverages U-Net-based generators and convolutional discriminators, optimized using adversarial, cycle-consistency, and identity losses. Results show high-fidelity translations that preserve anatomical structure, offering potential for clinical augmentation and data synthesis.

Introduction

MRI scans provide rich anatomical detail through various imaging modalities. T1-weighted images highlight fat and anatomical structure, while T2-weighted images emphasize fluid and pathology. In clinical practice, both modalities are often required, but acquiring them can be resource-intensive and expensive. Recent advances in deep learning, particularly Cycle-Consistent Generative Adversarial Networks (CycleGANs), offer a promising solution for cross-modality image synthesis. CycleGANs enable unpaired image-to-image translation by learning bidirectional mappings between domains while preserving structural consistency through cycle-consistency loss.

This project applies CycleGANs to translate between T1 and T2 MRI modalities, aiming to generate realistic images of one modality from the other. The approach has potential to reduce scan time, augment datasets, and support clinical decision-making when one modality is unavailable.

Project Objectives

The primary objective of this project is to develop a deep learning framework capable of performing style transfer between T1-weighted and T2-weighted MRI scans using a CycleGAN architecture.

The specific goals of the project are:

1. **Modality Translation:** To enable bidirectional translation between T1 and T2 MRI modalities, allowing the synthesis of missing or unavailable scans based on the available modality.

2. **Preservation of Anatomical Fidelity:** To ensure that the translated images retain the structural and anatomical integrity of the original scans.

3. **Unpaired Image-to-Image Learning:** To leverage the CycleGAN framework for training on unpaired datasets.

4. **Cycle Consistency Enforcement:** To implement cycle-consistency loss that ensures reversibility of translation (i.e., T1 → T2 → T1 and T2 → T1 → T2).

5. **Evaluation of Translation Quality:** To qualitatively assess the realism and consistency of generated images through visual inspection and cycle-reconstruction outputs.

By achieving these objectives, the project aims to demonstrate the feasibility and utility of CycleGANs in medical imaging, particularly in scenarios where multi-modal data acquisition is limited or infeasible.

Data Sources and Preprocessing

The dataset used in this project comprises a total of **89 grayscale MRI scan images** of human brain, split into **43 T1-weighted** and **46 T2-weighted** images. These images were sourced from a publicly available MRI scan repository and represent axial brain slices. Each image was pre-processed to ensure uniformity in size and intensity distribution:

- **Resolution:** All images were resized to **64x64x1 pixels** to reduce computational complexity and memory usage during training.

- **Normalization:** Pixel values were scaled to the **[0, 1] range** to stabilize training and improve convergence.

- **Format:** Images were converted to single-channel grayscale tensors compatible with TensorFlow pipelines.

The dataset was loaded using TensorFlow's tf.data.Dataset API, enabling efficient batching, shuffling, and augmentation. Although the dataset is relatively small, it was sufficient to demonstrate the feasibility of modality translation using CycleGAN. The unpaired nature of the data aligns well with the CycleGAN framework, which does not require pixel-wise correspondence between T1 and T2 images.

System Architecture and Design

The system architecture is based on the **CycleGAN** framework, which is specifically designed for unpaired image-to-image translation. In the context of this project, the goal is to learn mappings between two distinct MRI modalities—T1-weighted and T2-weighted scans—without requiring paired training data. The architecture consists of two main components: generators and discriminators, each responsible for different aspects of the translation process.

Overview of CycleGAN Design

CycleGAN employs a dual-generator and dual-discriminator setup:

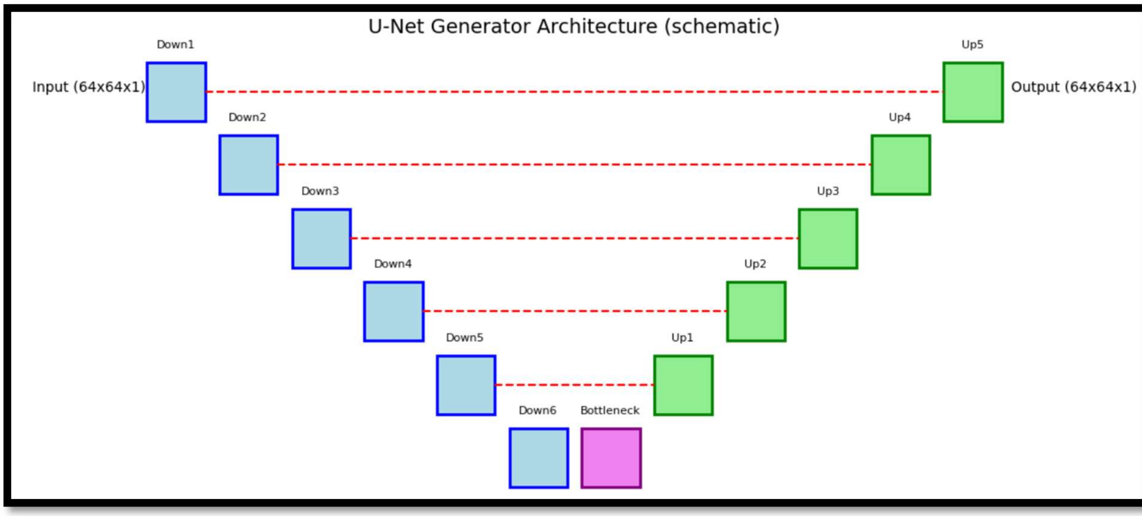
- **Generator G**: Translates images from domain T1 to domain T2.
- **Generator F**: Translates images from domain T2 to domain T1.
- **Discriminator Dx**: Distinguishes real T2 images from those generated by G.
- **Discriminator Dy**: Distinguishes real T1 images from those generated by F.

This bidirectional design enables cycle-consistency, ensuring that an image translated from one domain to another and back again remains structurally consistent.

Generator Architecture

Each generator follows a **U-Net** like architecture, which is well-suited for medical image translation due to its ability to preserve spatial features through skip connections. The generator includes:

- **Downsampling layers**: A series of 7 convolutional blocks with instance normalization and LeakyReLU activation, reducing spatial dimensions while increasing feature depth.
- **Bottleneck layer**: A compact 1x1 latent representation capturing modality-specific features.
- **Upsampling layers**: A series of 6 transposed convolutional layers that reconstruct the image, with skip connections from corresponding downsampling layers to retain fine-grained details.

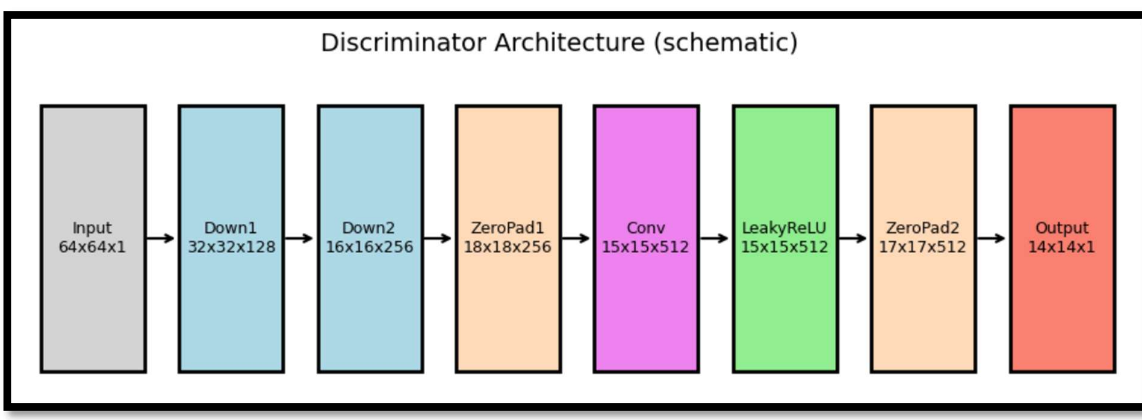


The output is a single-channel grayscale image of size 64x64x1, same as the input resolution.

Discriminator Architecture

The discriminators are designed as **PatchGANs**, which evaluate the realism of local image patches rather than the entire image. This approach is computationally efficient and effective for texture-level discrimination. Each discriminator includes:

- 5 convolutional layers with instance normalization and LeakyReLU activation.
- Zero-padding to maintain spatial dimensions.
- A final convolutional layer producing a patch-level real/fake prediction map.



Loss Functions

The system is trained using a combination of three loss functions:

- **Adversarial Loss**: Encourages generators to produce images indistinguishable from real ones.

- **Cycle Consistency Loss**: Ensures that translating an image to the other domain and back yields the original image.
- **Identity Loss**: Helps preserve colour and intensity when the input already belongs to the target domain.

These losses are balanced using empirically chosen weights to stabilize training and improve convergence.

Training Procedure

The training process involves simultaneous updates to two generators and two discriminators, guided by a combination of adversarial, cycle-consistency, and identity losses. The training is implemented using TensorFlow and executed over multiple epochs to ensure convergence and stability.

Training Configuration

- **Epochs**: The model is trained for **250 epochs**, allowing sufficient time for the generators and discriminators to learn stable mappings.
- **Batch Size**: A batch size of **8** is used to balance memory efficiency and gradient stability.
- **Optimizer**: The **Adam optimizer** is employed with a learning rate of **2e-4** and **β_1 = 0.5**, which is standard for GAN training.
- **Loss Weights**:
    - Adversarial loss: Encourages realism in generated images.
    - Cycle-consistency loss: Weighted to enforce reversibility.
    - Identity loss: Helps preserve modality-specific features.

Training Loop

Each training step involves the following sequence:

1. **Forward Pass**:
    - Generator G translates T1 → T2.
    - Generator F translates T2 → T1.

    - Cycle reconstructions are computed: T1 → T2 → T1 and T2 → T1 → T2.
    - Identity mappings are computed: T1 → T1 and T2 → T2.
2. **Discriminator Evaluation**:
    - Discriminator Dx evaluates real T2 and fake T2 (from G).
    - Discriminator Dy evaluates real T1 and fake T1 (from F).
3. **Loss Computation**:
    - Adversarial loss for both generators.
    - Cycle-consistency loss for both domains.
    - Identity loss for both domains.
    - Discriminator losses for real vs. fake classification.
4. **Gradient Calculation and Update**:
    - Gradients are computed using tf.GradientTape.
    - Parameters of generators and discriminators are updated accordingly.
5. **Checkpointing and Visualization**:
    - Model weights are saved periodically.
    - Sample outputs are generated and visualized to monitor progress.

Stability and Convergence

To ensure stable training:

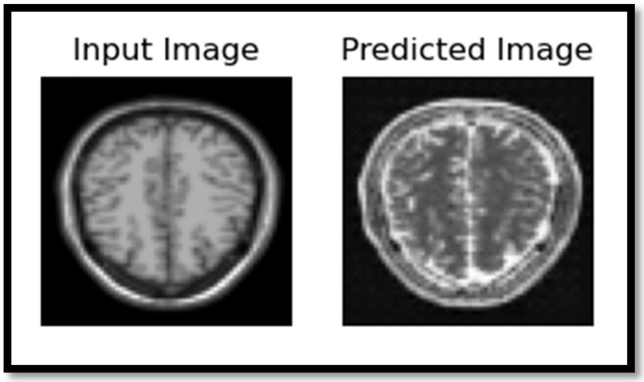
- Instance normalization is used instead of batch normalization.
- LeakyReLU activations help prevent vanishing gradients.
- Cycle-consistency loss prevents mode collapse and enforces structural integrity.

The training process is monitored using loss curves and visual inspection of generated images. Over time, the model learns to produce increasingly realistic translations while maintaining anatomical consistency.

Observations and Results

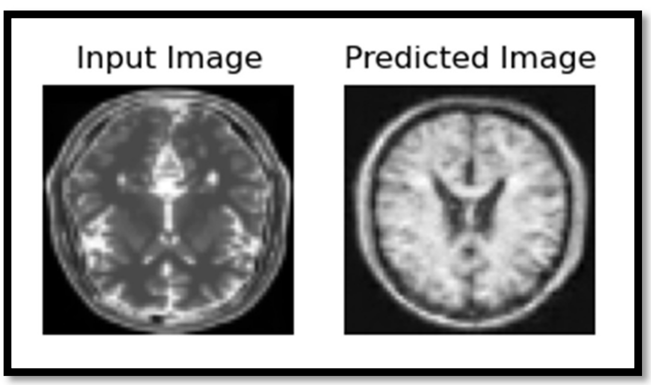
The model successfully translates T1 images to T2 images and vice versa. Visual inspection shows high anatomical fidelity and realistic texture synthesis. Sample outputs include:

- T1 → T2 translation:

  The generated T2 images exhibited fluid-sensitive contrast patterns typical of real T2 scans. Anatomical structures such as ventricles and cortical boundaries were preserved, indicating successful style transfer.

- T2 → T1 translation:

  The model effectively synthesized sharper anatomical detail, characteristic of T1-weighted images. The outputs were visually consistent with the target modality.

- Cycle-consistent reconstructions:

  The cycle-reconstructed images (e.g., T1 → T2 → T1) closely resembled the original inputs, demonstrating that the model learned reversible mappings. This consistency is crucial for medical applications, where structural fidelity must be maintained across transformations.

The generated images closely resemble their target modality, validating the model's effectiveness.

Challenges Faced

During the initial model development, there were some challenges which had impact on the model training and performance. But we have come up with proper resolutions to mitigate the issues faced.

Challenge	Resolution
Limited Dataset Size	Used data augmentation and regularization to reduce overfitting risk.
Lack of Paired Data	Leveraged CycleGAN's unpaired training capability and used cycle-consistency loss.
Training Instability	Applied instance normalization and carefully tuned loss weights and learning rates.
Anatomical Fidelity	Used identity and cycle-consistency losses to preserve structural features.
Computational Constraints	Reduced image resolution to 64x64x1 and optimized batch size for available hardware.

Future Enhancements

While the current implementation demonstrates the feasibility of MRI modality translation using CycleGAN, several avenues remain open for further exploration and enhancement:

1. Quantitative Evaluation: Future iterations should incorporate quantitative metrics such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Fréchet Inception Distance (FID) to objectively assess the quality and fidelity of generated images.

2. Scaling to Higher Resolutions: Scaling the architecture to handle clinical-grade resolutions (e.g., 256x256x3 or higher) would improve anatomical detail adding on to RGB colour configuration and make the outputs more suitable for diagnostic use.

3. 3D Volumetric Translation: Extending the model to work on 3D MRI volumes rather than 2D slices could capture spatial continuity across slices and improve realism in full scan reconstructions.

4. Pathology-Aware Translation: Incorporating pathological cases into the training data would allow the model to learn modality-specific representations of abnormalities, enhancing its clinical utility.

5. Multi-Modality Integration: Exploring multi-modal GANs that can translate between more than two modalities (e.g., T1, T2, FLAIR) could provide a more comprehensive synthesis framework.

Conclusion

This project successfully demonstrates the application of CycleGANs for unpaired image-to-image translation between T1-weighted and T2-weighted MRI modalities. By leveraging the cycle-consistency framework, the model learns to generate realistic representations of one modality from the other while preserving anatomical structure and contrast characteristics.

The results show that CycleGAN can effectively synthesize modality-specific features, enabling the generation of missing scans and potentially reducing the need for dual acquisitions in clinical workflows. The model's ability to maintain structural fidelity through cycle and identity losses is particularly valuable in medical imaging, where diagnostic accuracy depends on preserving fine anatomical details.

Despite limitations such as dataset size and resolution constraints, the project lays a strong foundation for future work in modality synthesis, data augmentation, and AI-assisted radiology. With further refinement, quantitative evaluation, and clinical validation, this approach could contribute meaningfully to faster, more efficient, and more accessible MRI diagnostics.