T1W MRI to T2W MRI Image Synthesis Using SSIM-CycleGAN

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***Abstract*—T1-weighted (T1W) and T2-weighted (T2W) sequences are common in MRI imaging, yet both are challenging to acquire efficiently. To optimize time and scanner availability, cross-modality image synthesis has emerged as a promising solution. The synthesis of T2-weighted MRI images from T1-weighted MRI images is essential in clinical practice, as it enables the extraction of valuable diagnostic information without requiring additional imaging sessions. Recently, CycleGAN networks have been widely utilized for synthesizing images from one modality to another due to their ability to be trained in an unsupervised manner. However, traditional CycleGANs often struggle to accurately capture structural and luminance information. Our proposed SSIM-CycleGAN integrates SSIM loss into the CycleGAN framework, resulting in a substantial improvement in the quality of the generated T2-weighted MRI images from T1-weighted MRI images. By focusing on structural similarity, this approach enhances both perceptual quality and clinical relevance. We conducted a detailed comparison of our method against existing techniques, and our proposed approach demonstrated significant improvements both quantitatively and qualitatively.**

***Index Terms*—SSIM-Structural Similarity Index, MRI-Magnetic Resonance Imaging, CycleGAN-Cycle Consistent Generative Adversarial Networks**

I. Introduction

T1-weighted (T1W)MRI highlights signals from fat tissue while minimizing those from water, whereas T2-weighted (T2W)MRI enhances the signals from water. Employing various contrasts in MRI allows for a more detailed evaluation of scanned organs. Nonetheless, obtaining all desired contrasts can be difficult due to constraints such as limited scan time, inadequate signal-to-noise ratios, and potential image artifacts. Recent advancements in deep learning have significantly increased the popularity of cross-modality image synthesis for generating medical images [12]. This innovative approach leverages complex algorithms to transform images from one modality to another, facilitating enhanced diagnostic capabilities and streamlining clinical workflows. By utilizing cross-modality synthesis, healthcare providers can derive valuable T2W images from existing T1W scans, maximizing the use of available data and improving patient care without the burden of additional imaging sessions [11]. This technique not only enhances diagnostic accuracy but also contributes to more efficient resource utilization in medical imaging. We developed an application for synthesizing T2W MRI images from T1W MRI images that incorporates SSIM loss into the existing CycleGAN framework to enhance the quality of synthesized images. By integrating this advanced loss function, we aimed to improve the perceptual fidelity of the generated images, resulting in outputs that better resemble the target images.

II. Related Works

With advancements in deep learning, cross-modality image synthesis has become an effective method for transforming T1 weighted(T1W) MRI images into T2 weighted(T2W) images. Various deep learning models, including CNN, GANs, pix2pix are employed for synthesizing multi-contrast MRI images. Recent advancements in generative adversarial networks (GANs), particularly CycleGANs, offer a promising approach for this task. The synthesis of T2W MRI images from T1W MRI images holds significant clinical value, providing additional diagnostic information without the need for additional imaging sessions [10]. The pix2pix model requires a substantial amount of paired data, which can be challenging to obtain in real-world scenarios, particularly for T1W and T2W MRI images. Any misalignment in the registration steps leads to inaccurate synthesis of images [2], [6].

The application of DC-CycleGAN for medical image translation has shown good results, but traditional loss functions often fail to capture perceptual quality [1], [3]–[5], [16]. In CycleGAN, the combination of L1 loss, adversarial loss, and cycle consistency loss often fails to adequately capture luminance and structural details in the synthesized images. Current models struggle to capture the structural details effectively, resulting in synthesized images that do not closely resemble the ground truth images. Due to the limitations of aforementioned methods, we have a developed a novel CycleGAN incorporating SSIM loss to avoid blurriness and preserving edge details in the synthesized images and maintain the luminance information. The SSIM loss provides a more effective measure of image similarity by focusing on luminance, contrast, and structure, which are essential in medical imaging. In this proposed work,we developed a model for synthesizing T1W MRI images to T2W MRI images using CycleGAN with SSIM loss in an unsupervised manner. An extensive study was conducted to compare our proposed method with existing techniques, evaluating its performance both quantitatively and qualitatively against the original CycleGAN. In addition to this, we conducted extensive evaluation of different loss function.

III. Methodology

A. SSIM-CycleGAN Overview

CycleGAN is one of the popular model for the cross-modality synthesis of medical images, particularly in transforming T1W MRI images into T2W MRI images. Our proposed architecture of our SSIM-CycleGAN is depicted in Figure 1. The CycleGAN architecture consists of two generators and two discriminators, enabling the model to not only generate T2W images from T1W inputs but also to ensure that the synthesized images can be transformed back to their original domain while retaining structural integrity. The inclusion of cycle consistency loss along with ssim, adversarial loss, and identity loss guarantees that the transformation is meaningful and reversible, preserving essential features that are critical for clinical assessment. By synthesizing T2W images from T1W images, CycleGAN not only reduces the need for additional imaging sessions but also provides clinicians with valuable diagnostic information, thus enhancing patient care and streamlining the imaging process.

B. CycleGAN Architecture

The CycleGAN model involve generators and discriminators, designed for image translation tasks between two domains. In our case, we translate T1-weighted MRI images to T2-weighted MRI images. U-Net architecture used as a generator and patchGAN served as a discriminator. U-Net consist of encoder and decoder in which downsampling operation performed convolution and max pooling operation and upsampling operations performed in decoder.

- **Generators:**
  - $G_{T1\to T2}$: This generator takes a T1-weighted MRI image x as input and produces a synthetic T2-weighted MRI image $G_{T1\to T2}(x)$.
  - $G_{T2\to T1}$: This generator takes a T2-weighted MRI image y as input and produces a synthetic T1-weighted MRI image $G_{T2\to T1}(y)$.
- **Discriminators:**
  - D_{T1}: This discriminator evaluates the authenticity of T1-weighted images, distinguishing between real images from the T1 domain and fake images generated by $G_{T2\to T1}$.
  - D_{T2}: This discriminator evaluates the authenticity of T2-weighted images, distinguishing between real images from the T2 domain and fake images generated by $G_{T1\to T2}$.

C. Loss Functions

1. Identity Loss

Identity loss ensures that when a generator receives an image from its own domain, it outputs an image close to the input image.

$$L_{\text{identity}}(x, G(x)) = \frac{1}{N}\sum_{i=1}^{N}\|x_i - G(x_i)\|_1 \quad (1)$$

where x is the input image, $G(x)$ is the generated image, N is the number of pixels in the image, and $\|\cdot\|_1$ denotes the L1 norm.

2. SSIM Loss

SSIM loss measures the structural similarity between two images.

$$L_{\text{SSIM}}(x, y) = 1 - \text{SSIM}(x, y) \quad (2)$$

where x is the ground truth image, y is the generated image, and $\text{SSIM}(x, y)$ is the Structural Similarity Index between x and y.

3. GAN Loss

GAN loss consists of generator and discriminator losses.

Generator Loss:

$$L_{\text{G}} = -\frac{1}{N}\sum_{i=1}^{N}\log(D(G(x_i))) \quad (3)$$

where D is the discriminator and $G(x_i)$ is the generated image from the input x_i.

Discriminator Loss:

$$L_{\text{D}} = -\frac{1}{N}\sum_{i=1}^{N}\left(\log(D(x_i)) + \log(1 - D(G(x_i)))\right) \quad (4)$$

4. Cycle Consistency Loss

Cycle consistency loss ensures that an image translated from one domain to another and back resembles the original image.

$$L_{\text{cyc}}(x, F(G(x))) = \|x - F(G(x))\|_1 \quad (5)$$

where F is the generator for the reverse transformation and G is the generator for the forward transformation.

Combined Loss Function

The overall loss function in a CycleGAN architecture can be defined as:

$$L_{\text{total}} = L_{\text{GAN}} + \lambda_1 L_{\text{SSIM}} + \lambda_2 L_{\text{cyc}} + \lambda_3 L_{\text{identity}} \quad (6)$$

where $\lambda_1, \lambda_2, \lambda_3$ are hyper-parameters that balance the contributions of each loss component.

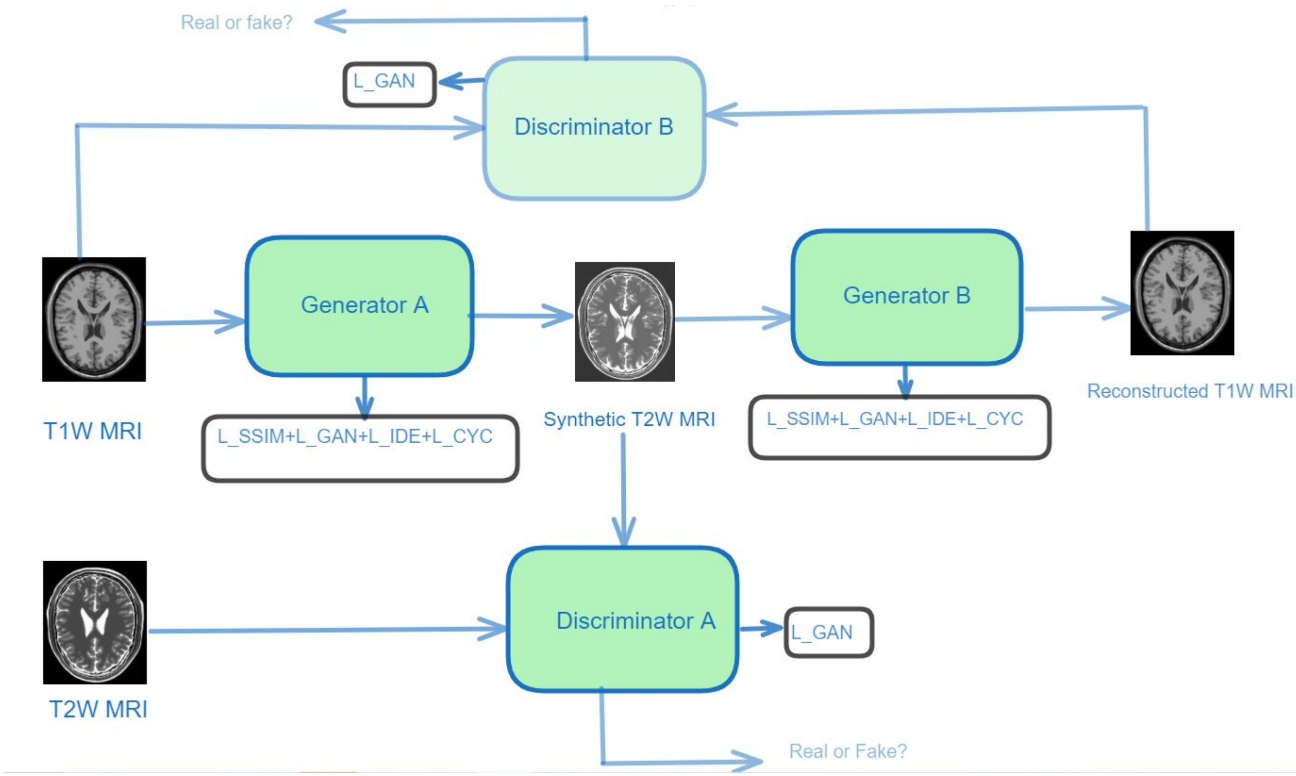

Fig. 1. Architecture of the proposed system.

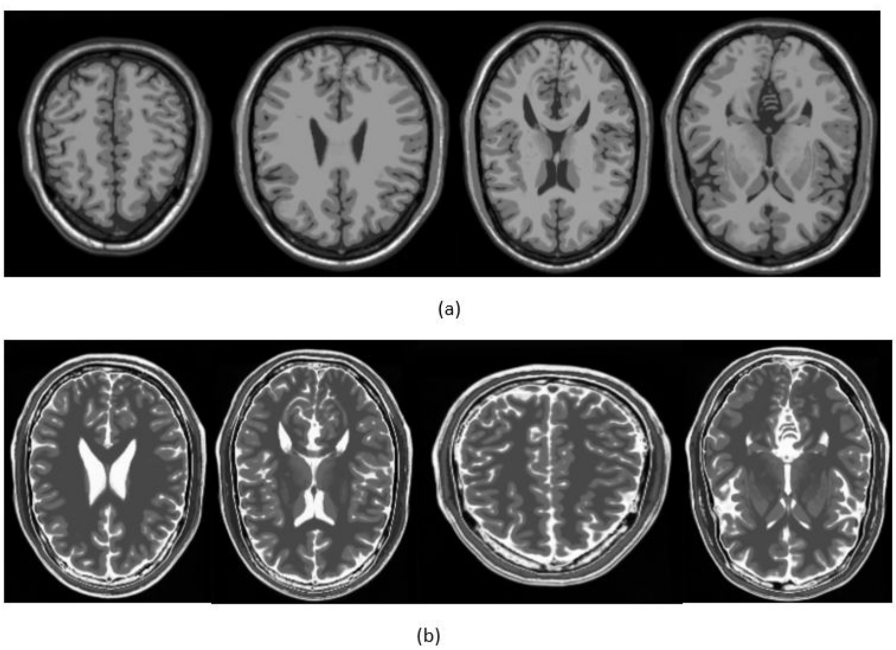

Fig. 2. Samples of images from the dataset(a) T1W MRI (b) T2W MRI

IV. EXPERIMENTAL SETUP

A. Dataset selection

Two public data sets are used to evaluate our model includes, BraTS-2019 and IXI dataset [11], [14]. Both dataset hosts a large collection of medical images, including T1W MRI ,T2W MRI scans from a diverse set of subjects. An unpaired dataset consisting of T1W and T2W MRI images is prepared from both datasets in addition to this pre-processing steps performed such as normalization and resizing to maintain consistency across inputs. Sample of images in our dataset are depicted in Figure 2. Paired data set is used for evaluation purpose.

B. Data pre-processing

Data pre-processing is a important stage in preparing MRI images with varying contrasts for tasks such as T1W to T2W MRI image synthesis using models like CycleGAN. Proper preprocessing can significantly enhance model performance. In our proposed method, we included a preprocessing step of normalization, where pixel intensity values are adjusted to a common scale, typically between 0 and 1 or -1 and 1. This process helps stabilize training and speeds up convergence. An example of normalization is given by the following equation:

$$\text{normalized\_image} = \frac{\text{image} - \text{mean}}{\text{std}} \tag{7}$$

C. Training Details

The model is trained over 250 epochs, with a batch size of 16 and an image size of 256x256. We used 80 percentage of the data for training and 20 percentage for testing, ensuring a balanced focus on GAN loss, cycle consistency loss, and SSIM loss. Regular validation was conducted to monitor performance and prevent overfitting. The Adam optimizer was used to minimize the loss functions, with learning rates carefully tuned to ensure stable convergence. Fine-tuning was performed to achieve faster convergence, allowing the model to adapt more efficiently to the data and optimize performance during training.

V. Results and Discussion

In this research, we created an SSIM-CycleGAN model to synthesize images between T1-weighted (T1W) and T2-weighted (T2W) brain MRI scans. We gathered and processed a large dataset of structural MRI images sourced from a publicly accessible database. Comprehensive experiments were performed to evaluate the performance of the SSIM-CycleGAN against the original CycleGAN. Both models were trained on unpaired images and assessed through visual evaluations and quantitative metrics, focusing on image synthesis quality, resilience with smaller datasets, and efficiency in terms of processing time.

A. Evaluation Measures for T1W to T2W MRI Synthesis

Peak Signal-to-Noise Ratio (PSNR): The Peak Signal-to-Noise Ratio (PSNR) measures the ratio of a signal's highest achievable power to the noise level that affects its integrity.

$$\text{PSNR} = 10 \log_{10}\left(\frac{R^2}{\text{MSE}}\right) \tag{8}$$

where R is the maximum possible pixel value (usually 255 for 8-bit images) and MSE is the Mean Squared Error between the synthesized and ground truth images.

TABLE I
Quantitative evaluation metrics using our proposed method

Samples	PSNR	MSE	MAE	SSIM
Sample 1	27.56	0.0841	0.1789	0.843
Sample 2	27.61	0.0843	0.1754	0.842
Sample 3	25.67	0.0849	0.1787	0.822

TABLE II
Quantitative evaluation metrics using different loss functions

LossFunctions	PSNR	MSE	MAE	SSIM
GAN+Cyc+SSIM+Iden(L1)	**28.66**	**0.0841**	**0.1706**	**0.846**
Iden+Cyc+GAN(L2)	23.61	0.0985	0.2942	0.804
SSIM+Cyc+GAN(L3)	27.55	0.0881	0.2367	0.842
Cyc+GAN(L4)	27.52	0.0887	0.1986	0.842

TABLE III
Quantitative evaluation metrics using different methods

Methods	PSNR	MSE	MAE	SSIM
SSIM-CycleGAN	**28.66**	**0.0841**	**0.1706**	**0.846**
DC-CycleGAN	26.61	0.0915	0.1867	0.814
CycleGAN(ResNet)	23.35	0.0981	0.1902	0.812

Structural Similarity Index (SSIM): SSIM assesses the visual impact of three characteristics: luminance, contrast, and structure.

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{9}$$

where μ_x and μ_y are the mean values of x and y, σ_x^2 and σ_y^2 are the variances, σ_{xy} is the covariance, and c_1, c_2 are constants to stabilize the division.

Mean Absolute Error (MAE): MAE measures the average magnitude of the errors between synthesized and ground truth images without considering their direction.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |x_i - y_i| \tag{10}$$

where x is the synthesized image and y is the ground truth image.

Mean Squared Error (MSE): MSE quantifies the average squared difference between the synthesized and ground truth images.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N} (x_i - y_i)^2 \tag{11}$$

B. Quantitative and Qualitative Evaluation

We conducted extensive comparisons between our proposed system and existing models. Our findings indicate that our system outperforms other models, achieving a Structural Similarity Index (SSIM) value of 0.846, a Peak Signal-to-Noise Ratio (PSNR) of 28.66 dB, and error metrics including Mean Squared Error (MSE) of 0.0841 and Mean Absolute Error

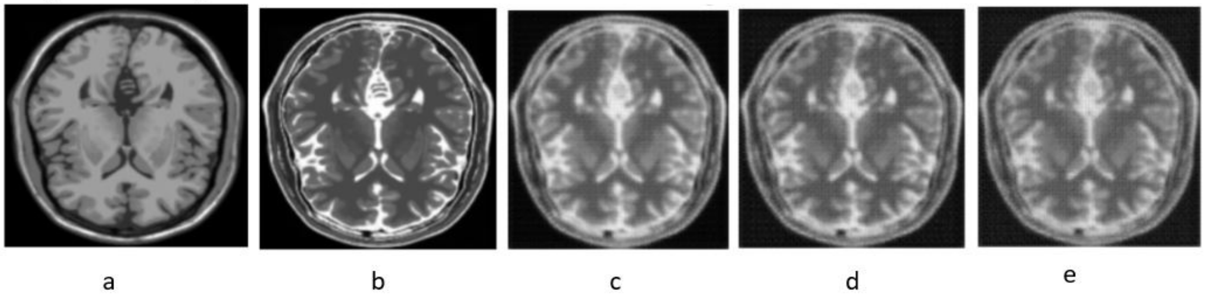

Fig. 3. (a) T1W MRI (b) Ground-truth T2W MRI (c) Synthetic T2W MRI using SSIM-CycleGAN (d) DC-CycleGAN (e) CycleGAN(ResNet)

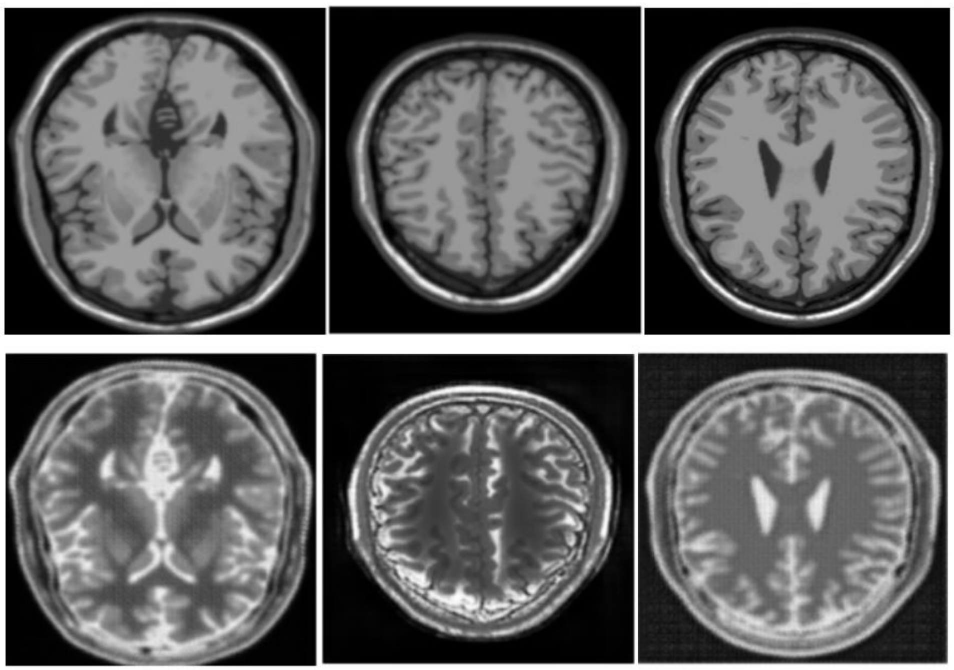

Fig. 4. Fist row represents the T1W MRI images and second row represents synthesized T2W MRI images

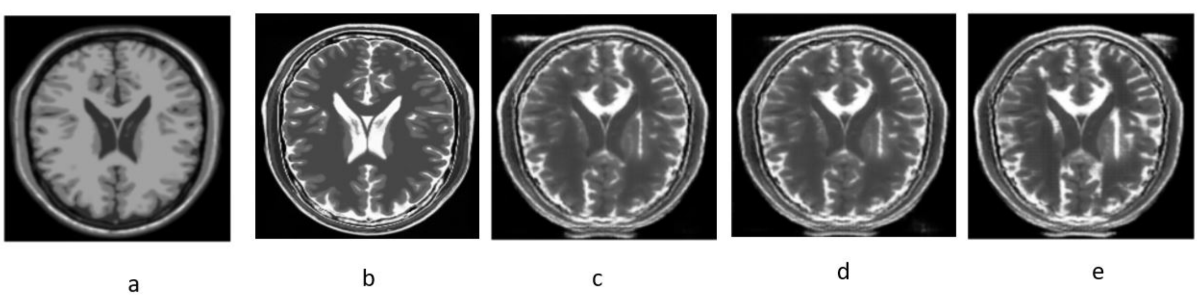

Fig. 5. Effects of different loss functions (a) T1W MRI (b) Synthetic T2W MRI using L1 loss (c) L2 loss (d) L3 loss (e) L4 loss

(MAE) of 0.1706. From Figure 3, the superiority of our proposed system is clearly visible. Additionally, the quantitative values presented in the accompanying Table 3 further underscore these results, demonstrating significant improvements in performance metrics. We reviewed the efficiency of our model using three sample cases. Quantitative evaluations are represented in Table 1. Qualitative evaluation represented in Figure 4.

In addition, we conducted an extensive comparison of our model's performance using different loss functions. We found that the combination of GAN loss, cycle consistency loss, SSIM loss, and identity loss yields the best results compared to other combinations. Notably, SSIM loss effectively captures fine details, resulting in synthesized images that closely resemble the original ones. From Figure 5 and Table 2, the results are clearly evident.

C. Discussion

Incorporating Structural Similarity Index (SSIM) loss into the CycleGAN framework significantly increase the visual fidelity of the synthesized images, particularly in the context of medical imaging tasks such as transforming T1-W MRI images to T2-W MRI images [16]. SSIM loss focuses on preserving the structural and perceptual characteristics of the images, ensuring that the generated outputs maintain important details and luminance information similar to the ground truth. By emphasizing structural similarity, this approach mitigates the shortcomings of traditional pixel-wise loss functions that often fail to capture the nuanced differences essential for accurate diagnosis. As a result, models that integrate SSIM loss alongside adversarial and cycle consistency losses produce images that not only appear more realistic but also offer improved diagnostic relevance. This dual focus on both adversarial training and perceptual quality allows for a more robust synthesis process, ultimately leading to better clinical outcomes in medical imaging applications.

Our proposed SSIM-CycleGAN enhances the visual quality of synthesized images but still struggles with structural inconsistencies. While incorporating SSIM loss captures luminance information effectively, it does not adequately address fine details. By integrating attention mechanisms and transfer learning, we aim to overcome the limitations posed by the current dataset size, thereby improving the accuracy and overall performance of our models.

VI. Conclusion

In this study, we developed an SSIM-CycleGAN model to synthesize T2W MRI images from T1W MRI. By integrating SSIM loss into the CycleGAN framework, we were able to effectively capture luminance information, leading to synthesized images that closely match the ground truth. Our proposed method outperformed existing frameworks in both quantitative and qualitative evaluations. We conducted a thorough comparison of various loss functions and found that SSIM loss excels at preserving fine image details. In the future, transfer learning could be incorporated to further enhance training and improve image synthesis quality. Additionally, our model has potential applications in other synthesis tasks.

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