A GAN-Based MRI Denoising Model for Alzheimer's Disease Using Free Attention and Wasserstein Loss

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***Abstract*—Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects the physical brain. Magnetic Resonance Imaging (MRI) is the gold standard in medical image analysis for detecting and monitoring the brain structure changes. However, MRI data acquisitions are often degraded by noise and have low resolution due to short scan times, hardware constraints, or patient motion. Previous research has addressed the problem using approaches such as spatial filtering, wavelet thresholding, and interpolation-based denoising, which can over-smooth the image. The noisy MRI regions lack reliable local features, which makes restoration difficult. Therefore, this research proposes a GAN-based framework for MRI denoising in AD. The proposed method integrates a free-parameter attention mechanism into the generator, while a wavelet-informed UNet discriminator is used. The Wasserstein loss with the gradient penalty was adopted to ensure a stable training. Our proposed model achieves a PSNR of 34.755 and SSIM of 0.9180, while minimising reconstruction error with an NRMSE of 0.1492 and MAE of 0.0151. The experiment's results demonstrate that the method surpasses existing GAN-based methods, such as RCA-GAN and OA-GAN. The quantitative and qualitative results confirm that the method effectively reduces noise while preserving anatomical details.**

***Index Terms*—Alzheimer's Disease, Generative AI, ADNI Dataset,**

I. Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects the physical brain. Magnetic Resonance Imaging (MRI) is the gold standard in medical image analysis for detecting and monitoring the brain structure changes [1]. However, MRI data acquisitions are often degraded by noise and have low resolution due to short scan times, hardware constraints, or patient motion. The degradations are harmful in AD analysis because the diagnostic relies on detail structure of MRI [2], [3]. The problem becomes a reason for the need for MRI denoising methods. Despite the recent research, the MRI denoising problem remains challenging because the noise is spatially non-uniform and overlaps with the main structural patterns. The traditional approach, such as spatial filtering, wavelet thresholding, and interpolation-based denoising, tends to over-smooth the image [4], [5]. The noisy MRI regions lack on reliable local features; it's making the restoration difficult. Deep learning methods, especially Generative Adversarial Network (GAN) based, have demonstrates a strong potential in medical image enhancement [6]–[11]. GAN-based model encourages the model to learn a realistic perceptual output for image enhancement. However, the GAN-based method suffers from unstable training, hallucinated structures, or insufficient image detail.

Several research attempted to address the issues, research [12] focuses on topology-aware using wavelet GAN. The approach introduces an additional parameter and does not balance between the structural fidelity and training stability. However, in the context of AD MRI, there are remaining gaps that need to be resolved: structure-aware, frequency-sensitive, and stable training processes. Motivated by the gaps, this research proposes a GAN-based framework for MRI denoising in AD. The proposed method has several contributions:

- Integrating free parameter attention mechanism [13] inside the generator section to emphasise the brain's anatomy without increasing model complexity.
- Deploying a wavelet-informed UNet discriminator to encourage preservation of high-frequency structural details relevant to Alzheimer's disease.
- Utilizing the Wasserstein loss with the gradient penalty to ensure a stable training.

The rest of the paper consists of Related Work, Method, Experiment, Result and Discussion, and Conclusion.

II. Related Work

Recent studies demonstrate the broad application of artificial intelligence (AI) across diverse domains, including healthcare, affective computing, autism, dementia, and education [14]–[17]. AI-based approaches have advanced COVID-19 chest X-ray analysis through optimisation-driven classification [18], deep transfer learning [19], and one-shot clustering [20]. AI has also been integrated with pervasive sensor-based patient management [21]. In addition, AI has been applied to EEG-based emotion recognition [22], psychological assessment [23], and dementia identification [24], [25]. AI has further supported secure healthcare infrastructure [26]–[28], fall monitoring [29], and smart education [30]. For the nerurological disorder detection, the methodologies range from foundational deep learning surveys [31] to high-precision ensemble methods, including 3D DenseNets [32] and Siamese networks for 4-way classification [33]–[35]. Research has further expanded into early detection using local field potentials [36], IoHT-based care frameworks [37], and multimodal prediction models [38]. Currently, a significant paradigm shift toward Explainable AI (XAI) emphasises clinical transparency, leveraging LIME and SHAP to ensure the interpretability of diagnostic models [39], [40]. In addition, generative models have been utilised within a unified representation learning framework [41], [42] and for multimodal brain data synthesis and analysis [43]–[45].

The GAN has shown promising results in MRI denoising, but during training, it suffers from instability, mode collapse, and vanishing gradients. The issue shows strongly in the medical imaging task. The causes are the dataset's limitations and the significant variation in noise distribution. Several studies are seeking to overcome this limitation by improving the adversarial loss function.

MedGAN introduces the adaptive training strategy by replacing the Jensen-Shannon divergence with the Wasserstein distance [7]. The proposed method improves the stability and convergence in generating medical images. TopoGAN [6] and HLSNC-GAN [8] incorporate topological constraints to preserve anatomical connectivity. The two algorithms employ the hinge loss and normalisation to stabilise the GAN process in medical image synthesis.

Although previous research improves training robustness, it was designed for image synthesis rather than MRI denoising. The denoising task in medical images relies on standard adversarial loss, which is sensitive to noise. Furthermore, the loss can lead to unstable training and inconsistent denoising performance. This research incorporates the Wasserstein loss function into an adversarial framework, thereby ensuring robust, stable training for MRI brain denoising.

MRI brain imaging is a gold standard and plays a crucial role in AD diagnosis. The MRI needs to capture brain structural changes, such as cortical thinning and hippocampal atrophy. The noise present during MRI acquisition obscures the brain's anatomical details. The problem motivates a researcher to use a learning-based denoising method rather than a conventional filtering method.

GAN-based approaches have been adopted for MRI denoising and image enhancement due to GANs' ability to preserve perceptual quality. The GAN method, such as Super Resolution GAN (SRGAN) and PLGAN, employs adversarial learning combined with perceptual loss to reduce noise in MRI. Shah et al. [46] utilise a Super-Resolution GAN (SRGAN) for medical image enhancement; the method demonstrates improvements in visual quality compared to a CNN-based denoising method. PLGAN follows a similar approach, integrating a perceptual loss to mitigate over-smoothing and enhance structural fidelity in MRI. However, the existing MRI GAN denoising method uniformly processes the entire image. The global approach needs to be modified for Alzheimer's MRI. Because the AD symptoms occur in a small region and

Algorithm 1 Training Procedure for MRI Super-Resolution GAN

Require: High-resolution MRI slices $\{I^{HR}\}$, degradation operator $\mathcal{D}(\cdot)$
Ensure: Trained generator G and discriminator D
Initialise parameters of generator G and discriminator D
for each epoch **do**
  Sample a mini-batch of high-resolution images $\{I^{HR}\}$
  Generate low-resolution images:
$$I^{LR} \leftarrow \mathcal{D}(I^{HR})$$
  Generate super-resolved images:
$$\hat{I}^{HR} \leftarrow G(I^{LR})$$
  Update discriminator D by minimising the discriminator loss
  Update generator G by minimising the generator loss
end for

are often overwhelmed by a dominant background structure. As a result, noise removal in the GAN method unintentionally degrades a diagnostically important region. To address the challenge, this research utilises an attention-based learning [13] inside the GAN's generator. The attention mechanism enables the network to focus on a disease-relevant brain structure during denoising.

III. Methodology

Figure 1 depicts the proposed method. The method used a GAN as a backbone with several enhancements. The method's components are: Generator Architecture, Discriminator Architecture, and Loss Function. Before explaining the model architecture, we need to look at the problem formulation. Let $I^{HR} \in \mathbb{R}^{H\ x\ H}$ denotes a clean high resolution of MRI slice and $I^{LR} \in \mathbb{R}^{H\ x\ H}$ as the degraded version. The degradation process consists of down- and upsampling MRI images with added noise. Equation 1 shows the process of MRI image degradation.

$$I^{LR} = D(I^{HR}) + \ \epsilon, \tag{1}$$

where $D(\cdot)$ denotes the down and up sample operator while ϵ is the Gaussian noise. The objective of the research is learning a mapping $G_0 : I^{LR} \rightarrow \acute{I}^{HR}$. The mapping reconstructs a degraded MRI slice into an HR MRI that closely matches the ground truth. The training algorithm of the paper is depicted in Algorithm 1.

The overall proposed method consists of a Residual in Residual Dense Block (RRDB) generator with free attention in between, a wavelet-informed UNet Discriminator, and a joint adversarial and reconstruction loss.

A. Generator Architecture

The generator utilises a residual-in-residual dense architecture to form three RRDB modules. Each module contains

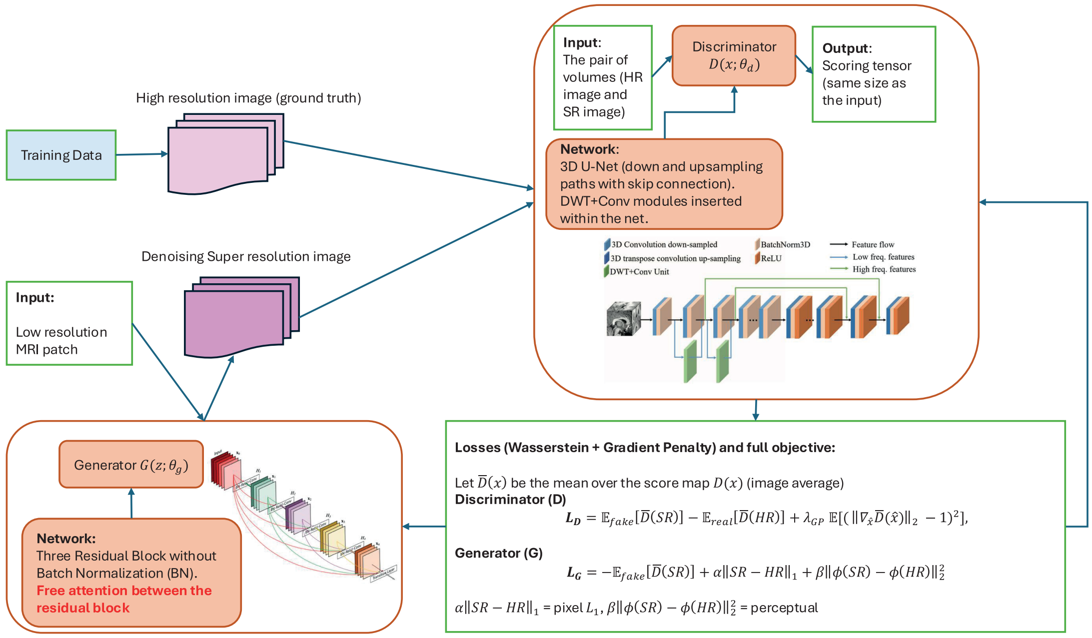

Fig. 1. Architecture of the proposed GAN-based MRI super-resolution framework, where low-resolution MRI patches are transformed into denoised super-resolved images using a residual-attention generator and a 3D U-Net discriminator, trained with a Wasserstein adversarial loss and reconstruction objectives.

multiple dense connected convolution layers without batch normalisation. The RRDB blocks stabilise the training and preserve the medical image distribution; the generator can be written as equation 2. F_{RRDB} denotes the stacked RRDB feature extraction and F_{Out} denotes the final reconstruction layer.

$$\hat{I}^{HR} = G_0(I^{LR}) = F_{Out}(F_{RRDB}(I^{LR})) \tag{1}$$

A free attention module has been inserted between RRDB modules in the generator to enhance feature extraction. Free attention computes the weight directly from feature variance and results in fewer parameters than the general attention.

B. Discriminator Architecture

The discriminator utilises a U-Net architecture to capture local texture and global structure. We employ a Discrete Wavelet Transform (DWT) in the downsampling part; it aims to model frequency-domain information. Discriminator is working by concatenating the two given inputs $(I^{HR}, \hat{I}^{HR})$. The DWT decomposes feature maps into low and high-frequency sub-bands (LL, LH, HL, HH). The decomposition enables the discriminator to focus on anatomical edges and limit unrealistic reconstruction. The wavelet guided discriminator encourages the generator to recover high-frequency MRI details, such as cortical boundaries.

C. Loss Function

The proposed model deploys the Wasserstein loss with the gradient penalty. Equation 2 shows the loss function for the discriminator, while Equation 3 explains the loss for the generator.

$$L_D = \mathbb{E}[D(x_f)] - \mathbb{E}[D(x_r)] + \lambda_{GP}\mathbb{E}(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2 \tag{2}$$

$$L_G = -\mathbb{E}[D(x_f)] + \lambda_1 \|I^{HR} - \hat{I}^{HR}\|_1 \tag{3}$$

Where $\mathbb{E}\left[D\left(x_f\right)\right] - \ \mathbb{E}\left[D\left(x_r\right)\right]$ is the Wasserstein loss, $\lambda_{GP}\mathbb{E}(\|\nabla\hat{x}D\hat{x}\|_2 - 1)^2$ is the gradient penalty, $-\mathbb{E}\left[D\left(x_f\right)\right] + \lambda_1$ is the adversarial loss, and $\lambda_1\|I^HR - \hat{I}^HR\|_1$ is the reconstruction. The discriminator loss consists of the Wasserstein objective that minimises the Wasserstein distance between the real and generated distributions. The gradient penalty is applied in the discriminator to enforce stability during training. The generator loss uses the adversarial loss to increase the critic on the fake pairs, while the reconstruction enforce the fidelity.

IV. Experimental Details

A. Dataset Description

The experiment uses the publicly available OASIS dataset [47]. OASIS is the cross-sectional MRI collected by the Medicine Department of Washington University. As shown in Table I, the dataset include 416 subjects, aged 18 to 96. Each subject has three T1-weighted MRI scans, and the raw image is available on their website. There are 100 subjects over 60 years old who have been diagnosed with AD, and the rest are normal. The dataset is stored in NIfTI format with two classes: AD and Normal. For the experiment, the dataset was split into 80% training, 10% validation, and 10% test.

TABLE I
DATASET DETAILS.

Characteristic	Detail
Total Subjects	416 individuals.
Age Range	18 to 96 years.
Hand Dominance	All subjects are right-handed.
Gender	Consists of men and women with nearly balanced numbers in each group.
Dementia Status	316 subjects without dementia and 100 subjects with a clinical diagnosis of AD (very mild to moderate).
Reliability Dataset	Includes 20 subjects without dementia who were rescanned within 90 days of the initial session.

B. Experimental Setup

The model trained under prepared setting, the used optimizer is Adam with the learning rate 2×10^{-4} , the number of batch size is four and the epoch is 50, then the best model is selected based on validation PSNR result. The performance is evaluated using four metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Absolute Error (MAE), and Normalised Root Mean Square Error (NRMSE).

V. RESULTS AND DISCUSSION

This section reports the performance of the proposed method in denoising brain MRI. The result was compared with the state-of-the-art method and trained under the same protocol. Table II presents performance metrics including PSNR, SSIM, NRMSE, and MAE. The proposed model achieves the best overall performance across all metrics. The proposed model is consistent in the PSNR and SSIM. The results indicate that the model enhances reconstruction fidelity and shows better structural preservation. On the other hand, the reduction in MAE demonstrates that the model accurately restores voxel-wise intensities. The restoration is critical for MRI interpretation.

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT MODELS

No	Model	Performance Evaluation			
		PSNR ↑	SSIM ↑	NRMSE ↓	MAE ↓
1	Proposed model	**34.755**	**0.9180**	0.14925	**0.01513**
2	DISGAN [12]	34.358	0.9148	0.34522	0.21813
3	GAN	7.592	0.1313	–	0.40547
4	OA-GAN [48]	27.7077	0.8751	0.0210	0.1620
5	RCA-GAN [49]	28.3025	0.8768	**0.0199**	0.1512
6	GCTNet [50]	27.8453	0.8689	0.0210	0.1594

Figure 2 depicts the qualitative comparisons of MRI denoising results among different models. The Low Resolution (LR) is the input that has been lowered and combined with the noisy blur. The LR image shows the low quality and blurred noise, which impacts the anatomical boundaries. The proposed method reduces noise and produces a sharper MRI image with clearer tissue. The image is closely similar to the ground truth.

The other state-of-the-art method generates smooth outputs. However, the image loses the partial anatomical details. The red circle in Figure 2 shows the section where the denoised image loses its structure. The qualitative results show that the proposed model can remove noise from the image. The model focuses on denoising around complex boundaries while minimising errors. The result indicates the model has a balanced trade-off between noise and detail preservation.

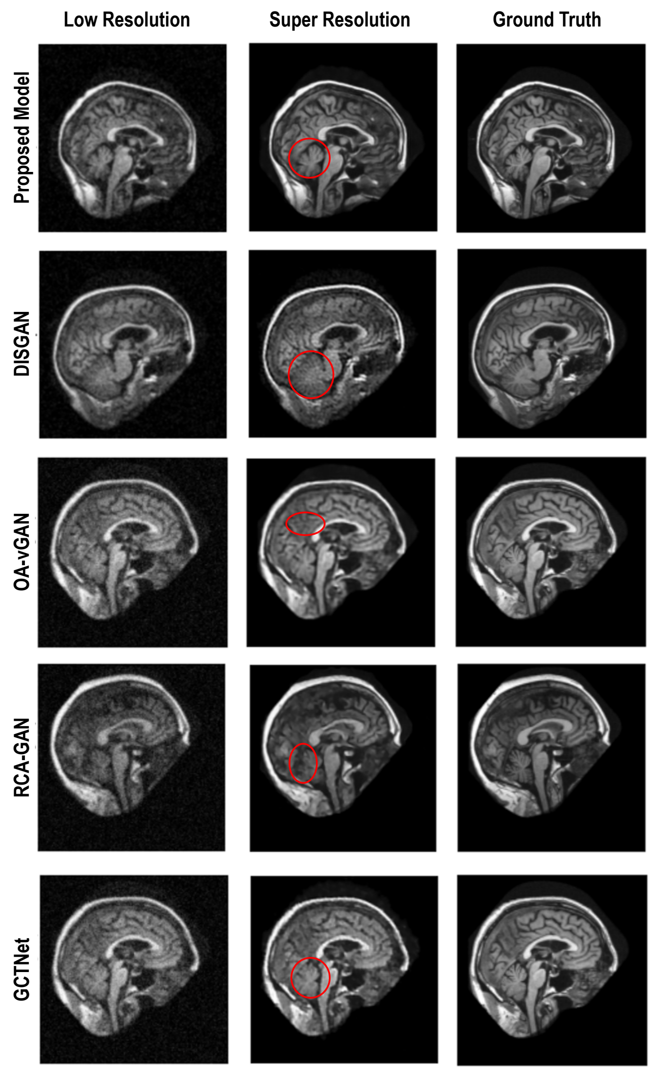

Fig. 2. Qualitative comparison of the denoising process using various methods. The red circle shows the difference between the super resolution and the ground truth.

Table III summarises the ablation study that was conducted on the proposed model. The ablation study assesses the contribution of each component. A1 is the condition without the attention module. Removing the attention-decreasing PSNR, NRMSE, and MAE, the generator can minimise the pixel-wise error. However, the SSIM is decreasing, indicating that attention helps preserve anatomical structure and boundaries. A2 is the scenario where the DWT is removed from the architecture. Removing the DWT slightly improves PSNR and SSIM; the results indicate that the DWT module needs further tuning to fully realise its benefits. A3 scenario removes the Wasserstein loss and uses the standard GAN loss. Wasserstein

TABLE III
ABLATION STUDY OF PROPOSED MODEL COMPONENTS

Exp.	Attn	DWT	Wass.	PSNR ↑	SSIM ↑	NRMSE ↓	MAE ↓
A0	1	1	1	27.746	0.868	0.0412	0.0225
A1	0	1	1	**28.102**	0.847	**0.0395**	**0.0214**
A2	1	0	1	27.919	**0.879**	0.0404	0.0216
A3	1	1	0	27.664	0.868	0.0417	0.0224

loss affects the training stability, realism constraint quality, and gradient behaviour. The PSNR degradation and the rising NRMSE indicate that the Wasserstein loss improves reconstruction quality and stabilises the learning process.

The findings highlight several important observations. The first is that attention integration between the RRDB generator improves the model's ability to capture anatomical details such as cortical boundaries. This is reflected in the improvement in SSIM and MAE compared with the other method. Secondly, the DWT helps preserve high-frequency details. DWT decomposes features into frequency sub-bands. The decomposition encourages the generator to recover anatomical structures rather than producing an overly smooth image. Without DWT module, in experiment A2, the model tends to train a low-frequency reconstruction. The image become visually smoother but lack in clinical meaningful details. Lastly, the use of Wasserstein loss with the gradient penalty contributes to stable training and improves the convergence behaviour. The loss provides smooth gradients and mitigates collapse during training. Overall, the proposed model balances local feature refinement, frequency-aware discrimination, and a stable training process.

VI. Conclusion

This paper presented a GAN-based framework for brain MRI denoising. The proposed method integrates three key components: 1) an attention mechanism between the RRDB block in the generator; 2) a wavelet-informed UNet discriminator; 3) A Wasserstein loss function. The experiment's results demonstrate that the method approach surpasses existing GAN-based methods such as RCA-GAN and OA-GAN. The quantitative and qualitative results confirm that the method effectively reduces noise while preserving anatomical details. The model characteristics make the proposed method a promising solution for practical MRI denoising tasks. Future work will explore the framework into multi slice and full 3D MRI denoising. Because the existing clinical dataset is highly diverse.

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