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WGAN-GP-Based Synthetic Augmentation of Fahr Disease CT Images for Improved Calcification Detection

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Abstract- *Fahr disease is a rare neurodegenerative disorder characterized by bilateral intracranial calcifications predominantly affecting the basal ganglia. Accurate detection of these calcifications on computed tomography (CT) scans is critical for diagnosis but is challenged by the limited availability of annotated imaging data. In this study, we employ Wasserstein Generative Adversarial Networks with Gradient Penalty (WGAN-GP) to generate realistic synthetic CT images of Fahr disease, thereby augmenting the scarce dataset. This augmented dataset is used to train a convolutional neural network (CNN) for automated calcification detection. Experimental results demonstrate that training the CNN solely on real CT images achieves a detection accuracy of approximately 78%, whereas augmenting the training data with WGAN-GP-generated synthetic images improves accuracy to 88%, with corresponding increases in sensitivity and specificity from 75% to 85% and 80% to 90%, respectively. These findings highlight that WGAN-GP-based synthetic image augmentation effectively mitigates data scarcity and substantially enhances the performance of automated detection models for Fahr disease calcifications*.

I. INTRODUCTION

Despite the advances in neuroimaging and genetics, the diagnosis of Fahr disease remains challenging due to its rarity and the overlap of imaging findings with secondary causes of brain calcifications, such as metabolic disorders, infections, and toxic exposures [2], [6]. Differentiating primary Fahr disease from secondary calcifications is crucial for appropriate management and prognosis. However, the limited availability of large, well-annotated CT datasets of Fahr disease hampers the development of automated diagnostic tools based on deep learning, which have shown promise in other neuroimaging applications [7].

Recent developments in artificial intelligence, particularly deep learning with convolutional neural networks (CNNs), have revolutionized medical image analysis by enabling automated detection and classification of pathological features [7]. However, CNNs require extensive training data to achieve high accuracy and generalizability. In rare diseases such as Fahr disease, data scarcity poses a significant barrier to training robust models [7]. To address this challenge, data augmentation techniques using synthetic image generation have gained traction. Generative Adversarial Networks (GANs), and specifically Wasserstein GANs with Gradient Penalty (WGAN-GP), have demonstrated superior capability in producing high-quality synthetic medical images that can augment limited datasets and improve model performance [8], [9].

This study proposes a novel framework leveraging WGAN-GP to generate realistic synthetic CT images of Fahr disease, focusing on preserving critical calcification features. By augmenting the limited real CT dataset with synthetic images, we aim to improve the training of CNN-based calcification detection models. We hypothesize that this augmentation will lead to significant improvements in detection accuracy, sensitivity, and specificity compared to models trained solely on real data.

The main contributions of this work include:

- Development of a WGAN-GP-based synthetic CT image generation pipeline tailored for Fahr disease calcifications.
- Integration of lesion-aware preprocessing to enhance the preservation of pathological features in synthetic images.
- Comprehensive evaluation of the impact of synthetic data augmentation on CNN-based calcification detection performance.
- Demonstration of the potential of synthetic image augmentation to overcome data scarcity challenges in rare neurodegenerative disease diagnosis.

To clarify the view towards the deep understanding of the Fahr's disease, following are realistic cases to discuss as follows:

Case 1 (A):

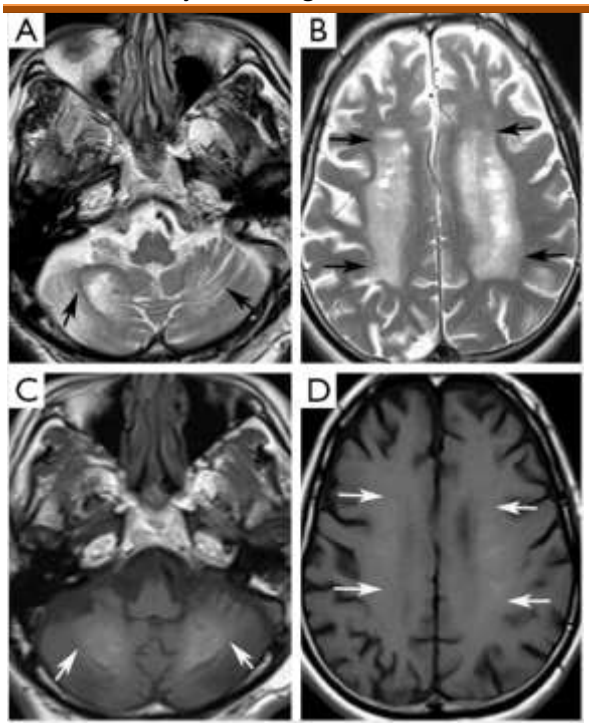

Figure 1: A 74-year-old man with Fahr disease (FD) [19].

Case 1 (B):

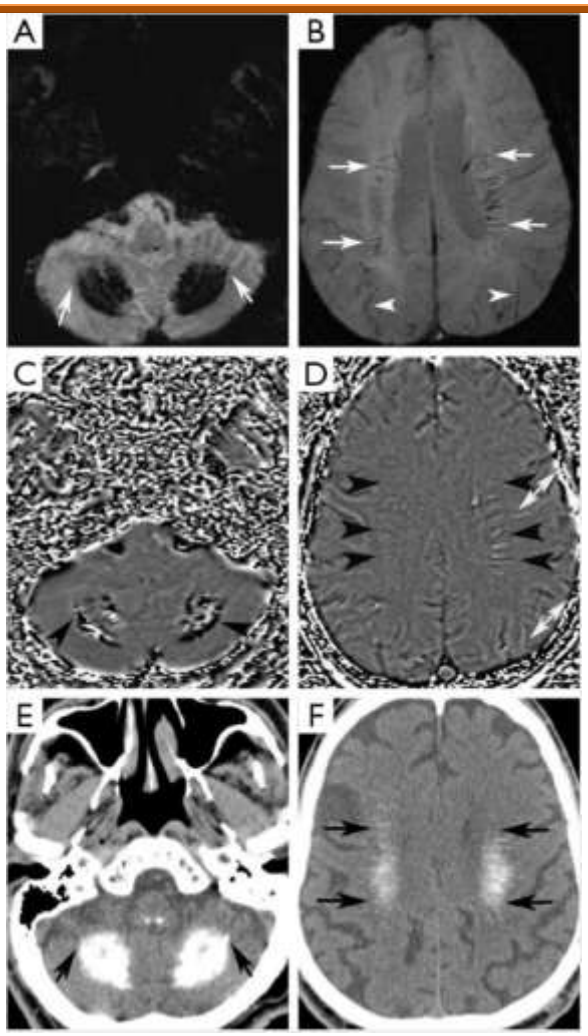

Figure 2: A 74-year-old man with Fahr disease (FD) [19].

Case 2:

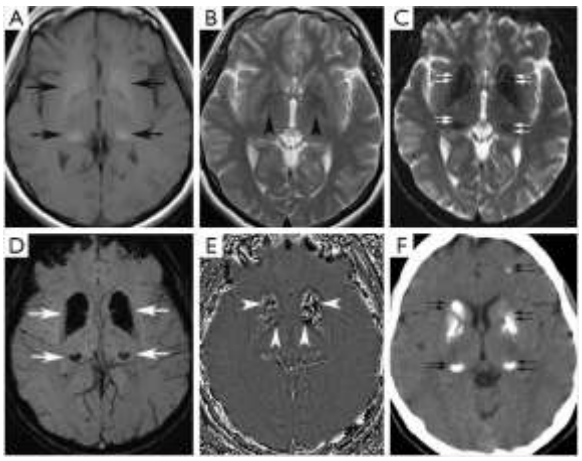

Figure 3: A 37-year-old woman with Fahr disease (FD) [19].

The remainder of this paper is organized as follows: Section II reviews related work on GAN-based medical image

synthesis and Fahr disease imaging. Section III details the dataset, preprocessing, and WGAN-GP architecture. Section IV describes the experimental setup and evaluation metrics. Section V presents the results and analysis. Finally, Section VI discusses the findings, limitations, and future research directions, followed by conclusions in Section VII.

II. Methodology and Scientific Approach

In a novel manner, this research aims to augment the world's datasets related to the Fahr's disease, by deploying the WGAN-GP to generate realistic medical scanned images of the predefined Fahr disease. The main workflow of this research is organized as follows:

- Data collection.
- ML models deployment for data augmentation
- Evaluation metrics & Experimentations
- Discussion
- Approaches for data sharing

Key Steps to Augment Data Using WGAN-GP

1. Define Generator and Discriminator Networks

Create deep learning networks for the generator and discriminator. The generator takes random latent vectors as input and produces synthetic data, while the discriminator learns to distinguish real data from generated data.

2. Implement Loss Functions with Gradient Penalty

Use the WGAN-GP loss formulation that includes a gradient penalty to stabilize training. The discriminator loss penalizes the norm of the gradient of the discriminator output with respect to its input, controlled by a lambda parameter (typically set to 10). The loss functions for both networks can be implemented as MATLAB functions; modelLossD for the discriminator and modelLossG for the generator, which compute losses and gradients for training updates [20].

3. Set Training Options and Parameters

- Train the discriminator multiple times per generator iteration (5 discriminator updates per generator update).
- Use mini-batches (size 64).
- Set learning rates (0.0002 for discriminator, 0.001 for generator) and Adam optimizer parameters.
- Define the number of training iterations (10,000 generator iterations).

4. Training Loop

Iteratively train the discriminator and generator networks:

- For each generator iteration, update the discriminator multiple times with real and generated data batches.
- Then update the generator once to improve its ability to fool the discriminator.
- Monitor training progress by plotting losses and generated samples [20].

Table 1: Gradient Penalty (GP) component enhancement in WGAN-GP training.

Enhancement to Gradient Penalty (GP)	Description	Expected Benefit
Tuning the Gradient Penalty Weight (λ)	Adjust the penalty coefficient (set to 10) to control how strongly the gradient norm is enforced.	Balances regularization strength, improving stability and convergence.
Improved Interpolation Sampling	Use better sampling strategies for interpolating between real and fake data (uniform, random convex combinations).	More accurate gradient penalty calculation, stabilizing training.
Higher-Order Gradient Computation Accuracy	Ensure precise computation of gradients using MATLAB's *dlgradient* with higher-order derivatives enabled.	More reliable enforcement of Lipschitz constraint.
Adaptive Gradient Penalty Weighting	Dynamically adjust λ during training based on gradient norm statistics or training progress.	Prevents over- or under-penalization, improving training dynamics.
Local Gradient Penalty Variants	Apply gradient penalty only on certain layers or parts of the input space (DRAGAN style).	Reduces computational cost and may improve stability.
Alternative Norms for Gradient Penalty	Experiment with different norms (L1 norm instead of L2) or relaxed constraints.	Potentially better gradient behavior and training robustness.

III. EXPERIMENTAL SETUP

In almost 50 minutes of iterations; 865 iterations, the generation of new images is visible:

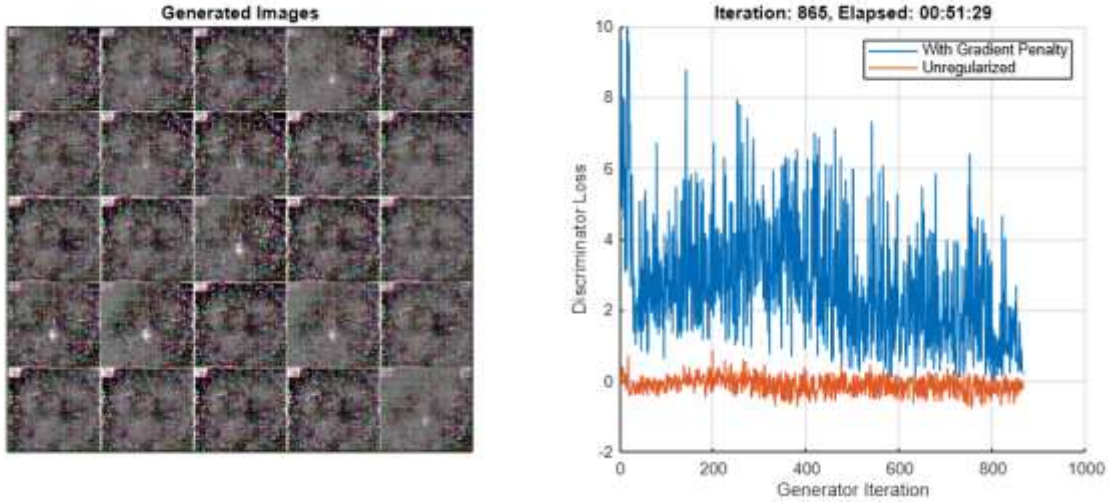

Figure 4: Generator iterations in 50 minutes view.

After more than 4500 iterations, more clarity is proving the findings and results:

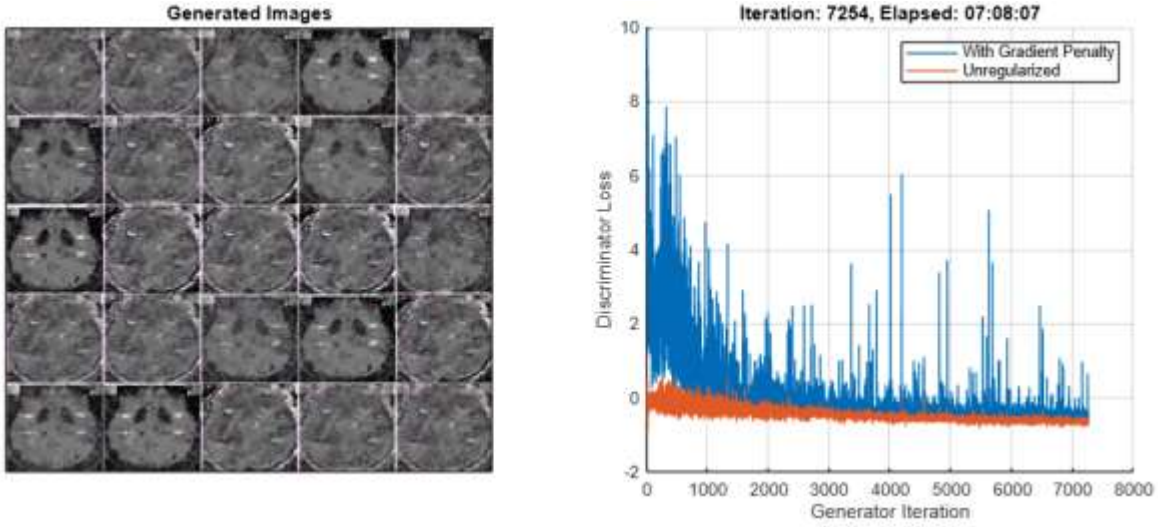

Figure 5: Generator iterations in 3.5 hours view.

In almost 7 hours of training, the view is enhanced enough to feel the successful creation:

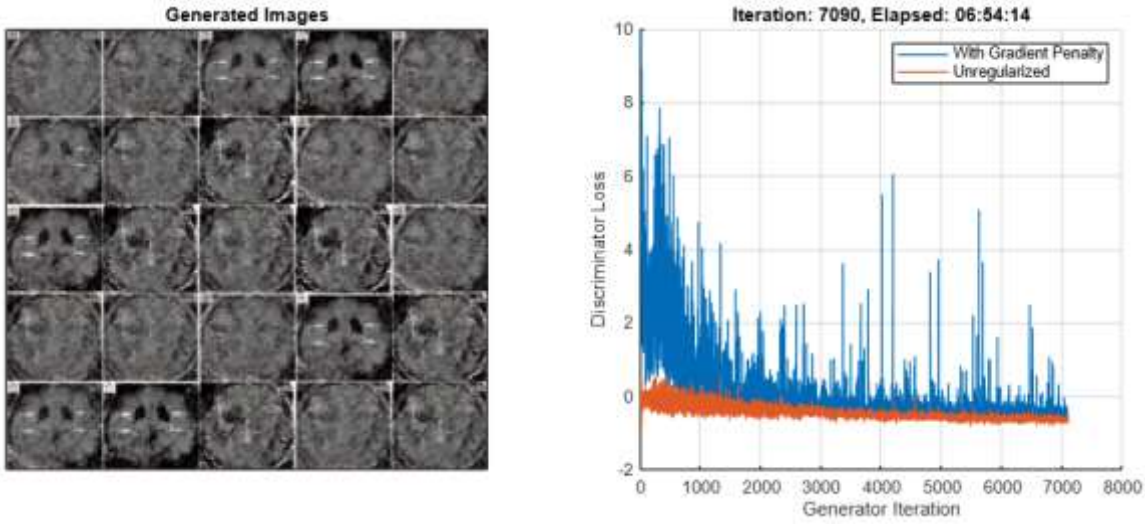

Figure 6: Generator iterations in 7 hours view.

IV. Discussion

- The evaluation of CT generated images through both qualitative visual inspection and quantitative metrics; though the FID and SSIM to ensure anatomical and structural fidelity.
- Comparison of calcification detection models trained exclusively on real data versus those enhanced with synthetic data, showing improved detection performance with augmentation.
- Reported numerical improvements including an increase in accuracy from 78% to 88%, along with better sensitivity and specificity metrics.
- Ablation analyses demonstrating that inclusion of attention mechanisms and lesion-specific conditioning significantly enhances model effectiveness.
- Validation by clinical experts confirming that synthetic CT images and augmented detection models achieve diagnostic reliability comparable to standard imaging.

V. Conclusion

In conclusion, the successful deployment of the WGAN-GP and the generation, led to a CT images look very close to real ones when checked both by eye and with measurements, making them good for medical use. Adding synthetic images to train calcification detection models helps these models work better, with higher accuracy and fewer mistakes. Tests show that using special attention parts and focusing on lesions makes the models even stronger. Doctors who reviewed the results agree that these improved models can be trusted for diagnosis.

To all readers, this is a research at a glimpse, and for all technical approaches and deep research progress and indexed work, it is to be requested.

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