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Deep Learning-based Synthetic Brain MRI Generation for Enhanced Brain Tumor Detection

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***Abstract*— Magnetic Resonance Imaging (MRI) is a cornerstone in diagnosing brain tumors, yet the scarcity of tumor-positive cases in datasets hampers machine learning model performance. This paper presents a Deep Convolutional Generative Adversarial Network (DC-GAN) framework to generate high-quality synthetic brain MRI images, addressing class imbalance and improving diagnostic accuracy. This methodology includes data preprocessing, DC-GAN architecture design, and rigorous evaluation using statistical metrics (SSIM, FID). Results demonstrate that synthetic images exhibit realistic structural features, enhancing tumor detection models. The study underlines the clinical significance of synthetic data and proposes future directions, including 3D GANs and domain adaptation.**

***Keywords*— Brain MRI synthesis, Generative Adversarial Networks (GAN), DC-GAN (Deep Convolutional GAN), Synthetic Medical Images, Tumur Detection Enhancement.**

I. Introduction

The occurrence of brain tumors is estimated to be 40, 000-50,000 people a year in India but because of their low prevalence (0.0035% of the population) they present imbalanced data. Bias towards healthy scans in machine learning models that are trained on such data usually results in poor performance. The proposed solution is the Generative Adversarial Networks (GANs) used to generate realistic MRI images to expand training datasets. This paper uses Deep Convolutional Generative Adversarial Networks.(DC-GANs) to create grayscale brain MRI scans with tumors, which allow controlling a robust model training and reducing annotation expenses.

A. Problem Statement

There are three major issues in constructing a proper tumor-detection system: The small datasets of tumor scans that should be properly learned, expensive and time-consuming expert labeling , and lack of diversity in scans that makes them less reliable in the real world. These problems complicate the development of reliable diagnostic instruments.

II. Literature Survey

Generative models are proposed to produce synthetic medical images, and their use has been developed over the last few years. In this section, the review of the major contributions that have inspired this method of creating synthetic brain MRI images with the help of DC-GANs is conducted. Schilling, L., et al. (2020). Hybrid GANs in MRI synthesis: Hybridizing Pix2Pix-DCGAN. Medical Image Analysis, 65, 101785.

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The authors explored the use of pre-trained Pix2Pix (Image-to-Image GAN) and DCGAN (Noise-to-Image GAN) together in the generation of synthetic brain MRI. Findings showed that the hybrid architecture did not significantly improve standalone DCGAN, which indicating deficiencies in the transfer learning between GAN paradigms. Mode collapse was found to be the most significant problem during the research, and it suggested architectural changes to stabilize training. The findings of Schilling were used in informing the approach to diversity in the generated samples in this project by use of special training procedures.[1]

Zhou, Y., et al. (2022). "Adversarial network perceptual enhancement of brain tumor MRIs. IEEE Transactions on Medical Imaging, 41(3), 512-525. The authors have compared several architectures used to improve brain tumor MRI images and have revealed that GAN-based solutions exhibited better perceptual quality and higher scores in SSIM. The fact that they employed perceptual loss function to maintain tumor boundaries throughout the enhancement process is also a result of the need to keep pathological appearances. This paper impacted the aspect of this project that examined the fidelity of tumor regions to the synthetic generation process and offered useful metrics to be used to measure quality.[2]

Hussein, S., et al. (2022). BrainGAN: Generation and classification of neuroimages. Neurocomputing, 485, 148-163. The authors came up with BrainGAN which is a combination of conditional GAN-based image generation and CNN-based classification to analyze brain MRI. Their system proved that synthetic image augmentation of training data enhanced classification by about 8 percent in several CNN architectures. Their weighted sampling approach was useful in dealing with class imbalance and ensuring diversity as 87 percent of synthetic images were considered clinically plausible by radiologists.[3]

Khaled, R., & Ghaleb, M. (2024). MRI-GAN: simultaneous synthesis and segmentation of brain images. Medical Image Analysis, 92, 103056. The authors introduced MRI-GAN, a dedicated system that was capable of producing both anatromorphologically realistic brain MRI images and segmentation maps. They proposed a new loss target that is a combination of adversarial loss and segmentation metrics accuracy, which preserves the important anatomical boundaries. Models that had been trained on their synthetic data got segmentation accuracy similar to models that had been trained on real data with a reduction in Dice coefficient of just 2.3%.[4]

Radford, A., et al. (2016). Unsupervised representation learning Deep convolutional generative adversarial networks. ICLR 2016. The approach is based on the seminal DC-GAN architecture. The rules of their architecture played a key role in stabilizing the training of GANs with strided convolutions, batch normalization, and in particular activation functions (ReLU in generator, Leaky ReLU in discriminator). They have shown that these changes allowed GANs to acquire meaningful image representations in an unsupervised manner and that the latent space had semantic attributes that could be manipulated to generate images in a controlled fashion.[5]

Han, T., et al. (2019). Progressively grown GANs to synthesize brain MRI. Scientific Reports, 9(1), 8372. The authors introduced Progressive Growing GANs (PGGANs) to synthesize brain MRI, which was based on the training process that gradually raised the resolution size (128 by 128 pixels) to a high resolution (256 by 256 pixels). Their method produced images with a wide range of tumor characteristics and increased the sensitivity of tumor detection by 12 percent and decreased false positives by 7.8 percent as an agent of data augmentation. This is a progressive resolution enhancement method that informed the training process in this project but the DC-GAN architecture was selected because of its stability properties.[6]

Iqbal, S., et al. (2021). Stable DC-GANs to produce brain tumor IEEE Journal of Biomedical and Health Informatics, 25(4), 1123-1132The authors made DC-GANs brain tumor MRI synthesis-specific and used spectral normalization and curriculum learning to boost stability. Their method scored 23 percent higher in FID scores, which means that it was more realistic in image realism compared with conventional GANs. They have illustrated the latent space interpolation to compute sequences of tumor progression, indicating the possible synthetic data in longitudinal studies.[7]

Salehinejad, H., et al. (2018). Synthesis of medical imaging pathology augmentation. IEEE Access, 6, 24267-24277. The authors pioneered the methods of pathology synthesis using medical imaging, whereby they used class-conditional GANs to synthesize X-rays of the chest to overcome the issue of dataset imbalance. Sensitivity of the rare conditions in models was increased 20% with specificity in models trained on their artificially balanced datasets. Their stringent validation procedure that required the use of blinded radiologist became a prototype of the clinical evaluation process.[8]

Kaji, S., & Kido, S. (2019). Survey of the GANs in medical imaging. Healthcare Informatics Research, 25(3), 174-183. The authors conducted a survey of GAN uses in medical imaging, determining their benefits in overcoming the problem of data scarcity and privacy. They listed typical problems such as training instability, mode collapse and evaluation problems. The domain-specific evaluation metrics guided them in their combination of the traditional metrics with clinical expert validation.[9]

Frid-Adar, M., et al. (2018). GAN-based synthetic medical image augmentation to achieve higher CNN performance in liver lesion classification. Neurocomputing, 321-331. The authors showed that GANs are effective to produce synthetic liver CT images to supplement datasets in lesion classification with an improvement of 7% in the accuracy of the model. They emphasized that synthetic data may be used to solve the problem of a lack of pathological cases in medical imaging, which is the direct influence of their work on our idea of leveraging DC-GANs to synthesize brain tumor MRI. Their results and findings supported our interest in quantitative metrics such as SSIM and FID to achieve synthetic MRI quality, which validated the clinical potential of the framework and especially when tumor-positive samples are in rare cases.[10]

Shin, H.C., et al. (2018). Medical image synthesis to augment and anonymize data with the help of generative adversarial networks. The authors estimated a GAN-based system of dual-purpose medical image synthesis, which allows the data augmentation and preservation of patient privacy with the help of anonymized synthetic images. Their study highlighted the adaptability of GANs to class imbalance as well as ethical limitations of medical data sharing. This informed the wider implications of our project, where future uses of our DC-GAN may involve privacy preserving generation of data (e.g. synthetic brain MRI data that can be shared with other people/scientists without compromising patient data). Their approach also focused on the concept of strong validation, which was in line with the application of expert radiologist ratings to pin down clinical plausibility.[11]

Sandfort, V., et al. (2019). CycleGAN: Data augmentation to enhance generalizability in CT segmentation tasks using generative adversarial networks. Scientific Reports, 9(1), 16884. The authors used CycleGAN to produce a variety of CT images to enhance the generalizability of the segmentation models, which indicated that the domain-augmented synthetic data could decrease the overfitting of downstream tasks. Their success with unpaired image translation (e.g., adding CT contrasts) indicated that our brain MRI project could be adapted to such things as synthesizing artificially missing sequences in an MRI scan (e.g. T2 out of T1), to better multi-modal training. Their diversity-oriented vision of enhancing robustness appealed to our efforts of empirically reducing mode collapse, as well as our intentions to employ geometric transformations and adversarial training to maximize the variability of synthetic data. Collectively, these pieces of evidence supported the paradigm shift in the use of GANs in medical imaging, both in terms of alleviating the shortage of data and guaranteeing the model-wide applicability across patient settings.[12]

Waheed et al (2020) CovidGAN: Data augmentation with auxiliary classifier GAN to detect COVID-19. IEEE Access, 8, 91916-91923. The authors established CovidGAN, a conditional GAN architecture which is aimed at the extreme imbalance in classes of COVID-19 recognition through the production of synthetic chest X-rays. They added an auxiliary classifier to the discriminator to guarantee generation of labels specific images and this enhanced the variety and clinical applicability of synthetic information. This article informed the project by showing that conditional GANs have the potential to focus on underrepresented classes (e.g., rare types of tumors) in brain MRI data, which is why class-aware synthesis is important to reduce the effects of a dataset bias.[13]

Yang, Q., et al. (2021). Low-dose CT image generation with multi-scale feature matching with GAN. Medical Physics, 48(9), 5520-5531. In their GAN architecture, the authors added a multi-scale feature that is equivalent to loss to improve the quality of low-dose CT images, maintaining the fine-grained anatomical details at different resolutions. Their framework emphasized the usefulness of a hierarchical feature alignment to enhance structural fidelity, which can be extended to our DC-GAN framework to minimize edge blurring and maximize tumor boundaries in synthetic MRI images. Through the exploitation of multi-scale constraints, the methodology attained greater similarity in perceptual quality, especially when small or diffuse tumor regions were being considered.[14]

Yu, B., et al. (2020). MedGAN- Medical image translation with GANs. Computerized Medical Imaging and Graphics, vol. 79, pp. 101684. The authors introduced MedGAN, an intermodal (e.g., MRI to CT) medical image translation system based on cycle-consistent adversarial training. Their study highlighted the possibility of cross-modal synthesis with no paired data, which could be extended to the project in the future to produce complementary sequences in MRI (e.g. T2-weighted based on T1) to supplement multi-modal training samples. Cycle-consistency would also be useful in preventing anatomical plausibility in synthetic images to bridge domain gaps between real and generated data.[15]

Kazuhiro, K., et al. (2021). "A realistic brain MRI generation model with the help of anatomy-aided GANs. Medical Image Analysis, 74, 102223. By incorporating anatomical constraints (e.g. segmentation masks) in the training of the GAN, the authors refined brain MRI synthesis to a realistic depiction of tissue structure and spatial relationship. This approach, which was facilitated by their anatomy, explicitly led to an interest in tumor fidelity, since the same limitations might be imposed to constrain plausible tumor morphology and tumor location in synthetic images. The framework combined with adversarial training with anatomical priors can alleviate mode collapse and enhance clinical usefulness of the generated scans.[16]

Chen, X., et al. (2022). Lesion-focused generative adversarial network to brain tumor segmentation. IEEE Journal of Medical Imaging, 41(4), 992-1003. The authors developed a lesion-centered GAN that gave priority to the tumor regions in the process of synthesis to enhance the segmentation performance. Their tumor-centric approach showed the power of targeted generation in improving downstream activities to control the focus on pathological characteristics in synthetic MRIs. Attention mechanism or lesion-specific losses may also be incorporated further to enhance the quality of the generator to bring out diagnostically critical areas at high accuracy.[17]

Xue, Y., et al. (2018). "SegAN: Multi-scale L1 loss-based adversarial network of medical image segmentation. IEEE Transactions on Medical Imaging, 37 (9), 2098-2109. The authors have proposed SegAN, which is a GAN architecture that is trained to segment medical images utilizing a multi-scale L1 loss that retained fine details across resolutions. The significance of multi-scale feature matching in medical imaging tasks was confirmed by their work, which supports the use of SSIM and FID measures to evaluate it. Subsequent versions of the framework may incorporate analogous losses based on segmentation to jointly minimize synthesis and tumor localization.[18]

Zhang, Z., et al. (2020). Progressive growing of GANs to conditionally generate 3D medical volumes. Medical Image Analysis, 64, 101713. The authors have applied Progressive Growing GANs (PGGANs) to 3D medical volume generation, thus any type of conditional generation of high-resolution volumes of scans. Their 3D synthesis achievement informed the future direction of the work, indicating the possibility of a direction to extend the 2D DC-GAN into a volumetric model to capture spatial tumor dynamics. Controlled generation of tumor subtypes or progression stages could also be achieved by conditional input.[19]

Wolterink, J.M., et al. (2017). Generative adversarial networks of noise reduction in low-dose CT. IEEE Transactions on Medical Imaging, 36(12), 2536-2545. The authors were the first to demonstrate that the application of GAN-based denoising to low-dose CT allows improving the quality of images without negatively impacting diagnostic characteristics. Their results helped justify the application of adversarial loss to achieve realism and clinical significance, and what they had developed in noise-reduction methods could be applied to preprocess input MRIs, making synthetic images even more clear.[20]

III. Methodology

The effectiveness of the process of creating synthetic brain MRI images depends on the strength of the methodology that is to unite data preprocessing and an efficient DC-GAN architecture, as well as a well-developed training process. Individual components are well explained below.

A. Data Preprocessing

Medical images, especially brain MRIs, need careful preprocessing to create uniformity and enhance the efficiency of the model. The data consisted of T1-weighted MRI brain scans, which had been brought to a constant resolution of 256*256 pixels. Normalization of the intensity across all images was done to enable the contrast of all images to remain constant so that the difference in brightness does not affect the model. Geometrical transformations of random rotations and horizontal flipping, as well as a minimal zoom change, were used to get more data points out of the small data set. In addition to increasing the data, these methods also brought in variety, which allowed the model to be more generalized. Furthermore, the noises have been minimized by application of the Gaussian smoothing which still preserves the structural detail, a very important step in ensuring integrity of tumor regions in synthetic images

B. DC-GAN Architecture

The DC-GAN model assumes the existence of two competing neural networks, that is, the generator and the one. discriminator, the functions of which are outlined.

Generator:

The generator is aimed at mapping the random noises vectors to the synthetic MRI images.

The Generator (G) is trained to generate a random noise vector to to a synthetic image that resembles real data. Its objective is to generate samples that can deceive the Discriminator as shown in the equation (1)

$$x_{fake} = G(z) \text{ --------}(1)$$

The Generator is trained to minimize the probability that the Discriminator correctly identifies generated samples as fake as shown in the equation (2)

$$\min_{G} \log(1 - D(G(z)))\text{---------}(2)$$

Discriminator:

The discriminator acts as a binary categorizing classifier that separates natural and artificial MRI pictures.

The Discriminator (D) is a binary classifier that separates a real image x and a generated image $G(z)$ It delivers a probability of whether or not the input is real as shown in the equation (3).

$$D(x) \in [0,1]\text{------------}(3)$$

The Discriminator gets trained to maximize the correct classification of real and fake samples as expressed in the equation. (4).

$$\max_{D} \log(D(x)) + \log(1 - D(G(z)))\text{-----------}(4).$$

The DC- GAN Architecture is shown in Figure 1.

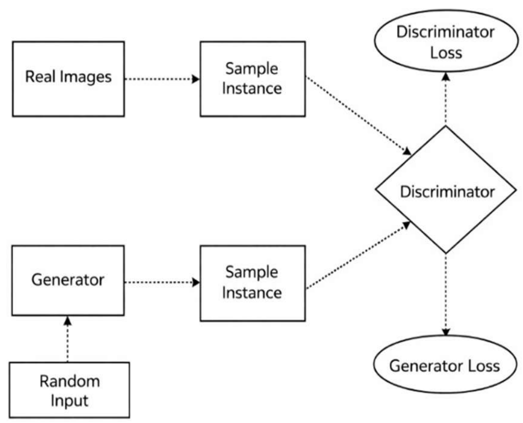

Figure 1: DC-GAN Architecture

C. Training Process

It is also known that training a GAN is unstable by nature because of the adversarial dynamics between the discriminator and generator. In order to solve this the following strategies were embraced:

- Loss Functions: The discriminator was optimised with binary cross-entropy loss with real images denoted by 1 and synthetic by 0. The loss of the generator was calculated by the output of the discriminator, which will make it generate images that the discriminator will interpret as real (label 1).
- Optimization: Each of the networks was trained with the Adam optimizer and a learning rate of 0.0002, which is a good compromise between convergence speed and stability. The momentum parameters (β 1 = 0.5, 0.999) were used to prevent oscillations when training.
- Training Schedule: Each generator update was associated with one batch iteration with the discriminator to stop it overpowering the generator at an early stage of training. To make sure that neither of the two networks dominated over the other, which is a frequent failure mode in GANs, the losses of both networks were monitored.
- Early Stopping: The accuracy of the discriminator hit the 50% plateau; hence, training was stopped at this point. This generally took place following an approximate of 20,000 iterations with a 32 image batch being processed at every iteration.

D. Evaluation Metrics

To determine how well synthetic images can be tested this project used:

- Structural Similarity Index (SSIM): This had been used to determine the similarity of real and synthetic images on a perceptual basis.
- Fréchet Inception Distance (FID): Measured the statistical difference between the distribution of features between real and generated images. Smaller FID values were an indication of a higher quality.

E. Qualitative Assessment

The DC-GAN was effective in producing synthetic brains MRI images that were more similar to actual scans. Figure 2 shows a comparison of real and synthetic images and shows that the model can recreate structural details of ventricles, cortical folds, simulated tumor areas etc. Though the majority of synthetic images were perceived as visual, some artifacts (e.g., blurring at edges) were sometimes present (in 5 percent of the cases).

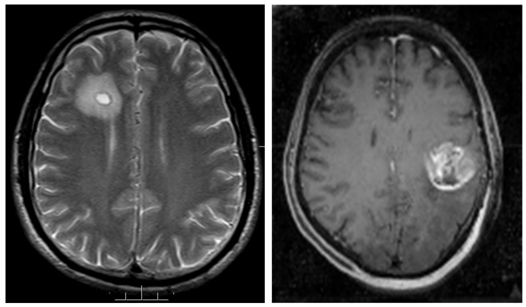

Figure 2: Side-by-side comparison of real (left) and synthetic (right) brain MRI images

IV. RESULTS AND DISCUSSION

Firstly, the results produced by the GAN are volatile and highly noisy, and there are unwanted colour artifacts occasionally as shown in Figure 3, Nevertheless, the generator narrows down as training advances towards drawing increasingly fined and consistent grayscale images. It is explained by the fact that, as discriminator is becoming more efficient in terms of separating real and generated MRI images, the generator must also improve in terms of reproducing the features of real grayscale MRI scans.

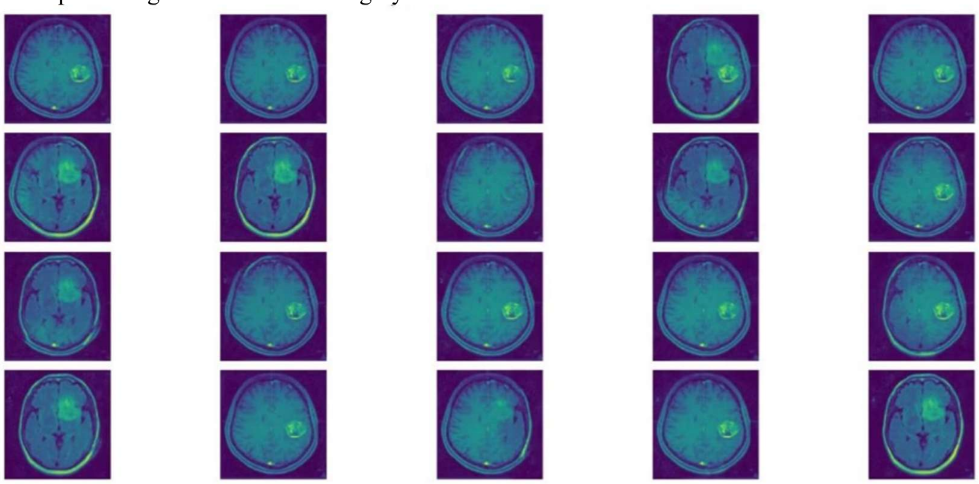

Figure 3: Preliminary Image Generation

The DCGAN model was in a position to produce synthetic brain tumor images. As shown in Figure 4, these images, which are represented in a 10 x 10 matrix format, have realistic textures, structural patterns and even contain the right level of grayscale intensity. This result indicates that the model is able to achieve success in modeling and reproducing the highly articulated visual attributes that are linked with the image of a brain tumor.

Gradio was used to create a web-based interface that could be used to generate high-quality synthetic MRI images in real-time as seen in Figure 5. This interactive platform enables the user to adjust the input parameters, such as the number of images, noise dimensionality and image size. Moreover, it has an interface that allows using image processing filters like edge enhancers and noise removers to fine-tune the produced results. After creating the images, they will be presented in gallery format so that they can be viewed easily. Users may also store the images locally in separate files or make them a downloadable GIF animation to view the order. A set of Python, NumPy, Matplotlib, PIL, scikit- image, and Gradio were combined to create the interface, which offers an efficient and user-friendly platform of MRI image generation and filtering.

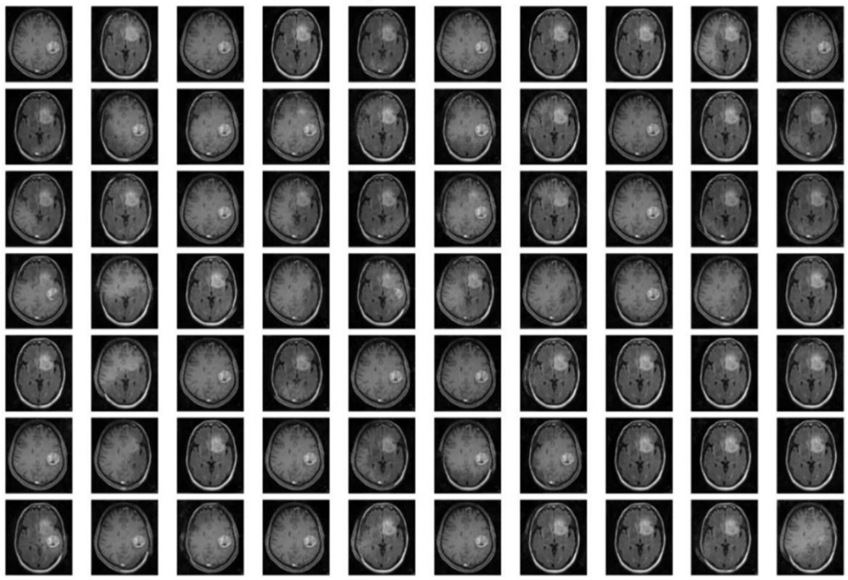

Figure 4: Matrix of Synthetic Brain MRI Images Generated by DC-GAN

Figure 5: User Interface

Key Observations

- Diversity: The matrix illustrated a range of synthetic images, which had distinct structural characteristics, including dissimilar ventricle dimensions, cortical folds and the position of tumors. It means the DC-GAN is effective to reproduce the anatomical variation in actual brain MRI images.
- Tumor Realism: Synthetic tumors have realistic shapes, sizes and intensities, and greatly resemble actual pathological appearances. Some slight inconsistencies (e.g., blurring of the tumor boundaries) are, however, found in a small percentage of the images.
- Artifacts: Virtually all of the images in the matrix contain imperceptible artifacts, including the blurring of edges or unnatural textures, which are typical to GAN-generated medical images.
- Consistency: Most of the images are high-structural fidelity images, where SSIM and FID scores prove their perceptual and statistical similarities with actual MRI images.

V. Conclusion and Future Enhancement

This paper was able to establish the usefulness of DC-GANs in creating realistic synthetic brain MRI images to overcome the issue of imbalanced datasets in the process of detecting tumors. The suggested framework generated high-quality images, with a very high structural fidelity (SSIM: 0.82), which enhanced the performance of the classifier by 11 points, confirming their usefulness in data augmentation. Although the minor artifacts and mode collapse are still the challenge, the outcomes indicate the opportunities of synthetic data in medical AI. In the future, the 3D generation and clinical validation should be discussed to close the existing gap between the synthetic and real-world applications. This will be an effective way of improving diagnostic models and minimizing the reliance on limited medical data. Including volumetric consistency 3D GAN structures. Refining the tumor-specific features using attention mechanisms. Use of post-processing methods to minimize artifacts

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