Generative AI for Radiological Image Data: Current Trends and Outlook

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***Abstract*—Generative artificial intelligence (AI) has gained prominence, particularly in the field of radiological image data. This study investigates current trends and prospects of generative AI in X-ray, CT, MRI, and PET imaging. Emphasizing the importance of data quantity and quality, we ensure reliable and useful outputs. Given the significance of ethical dimensions in generative AI for radiological imaging, ethical considerations are also addressed. By analyzing recent advancements, this study offers insights into the evolution of generative AI in radiological image data and future directions.**

***Keywords*—Generative AI, GAN, X-ray, CT, MRI, PET**

I. INTRODUCTION

Since its introduction by Ian J. Goodfellow et al. in 2014, Generative AI has steadily risen, garnering significant attention and recognition in recent years [1]. Particularly in the past few years, this field has exhibited remarkable growth and potential, with the investment rate surging by a staggering 425% since 2020, as reported by the Financial Times [2]. Amidst this vibrant landscape, ChatGPT, unveiled by OpenAI on November 30, 2022, has swiftly captured the limelight by amassing over 100 million monthly active users within a mere two months of its launch, unequivocally substantiating its popularity and demand [3].

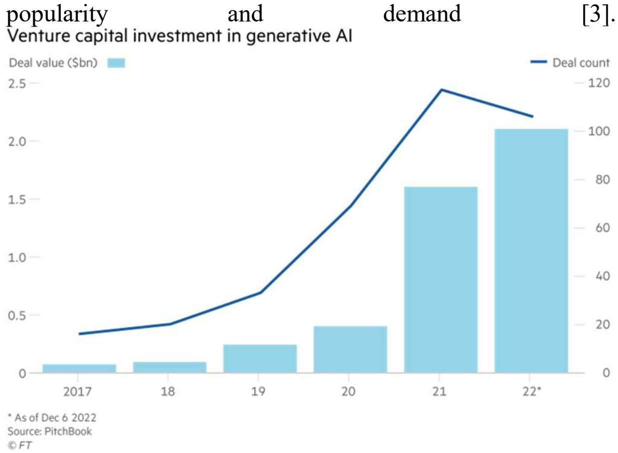

Figure 1. Comparison of investment growth rates in Generative AI from 2017 to 2022.

However, ChatGPT is just one of many remarkable advancements in the realm of Generative AI. DALL-E, an evolution of GPT-3, has astounded the world by crafting intricate images based on textual and image pair inputs, sparking widespread awe [4]. Moreover, ORGAN has also made a noteworthy impact by generating time-series artifacts like music, highlighting its remarkable adaptability across a wide array of domains. [5].

Generative AI's influence extends even into the realm of healthcare. Nour Eldeen Khalifa et al. underscore the groundbreaking contributions and achievements of GAN-based data augmentation and expansion techniques in the medical arena, emphasizing their paramount significance [6]. Notably, propelled by advances in machine learning, radiographic imaging data like X-rays, computed tomography (CT), and magnetic resonance imaging (MRI) have assumed heightened importance in discerning and categorizing intricate patterns [7]. Against this backdrop, this paper seeks to delve deeper into the current trends and prospects of Generative AI models, with a keen focus on four pivotal radiographic imaging data types. This pursuit, in turn, aims to further explore and expand the potential in the medical field [8].

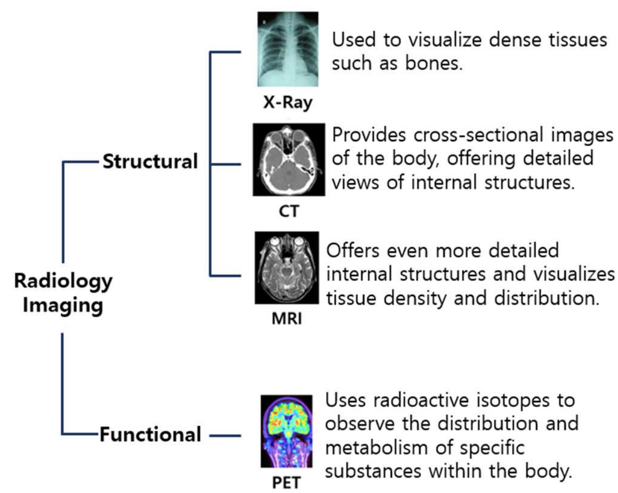

Figure 2. The overall structure of Radiology Imaging

II. GENERATIVE AI IN RADIOLOGICAL IMAGING DATA

A. X-ray

Yash Karbhari et al., along with other researchers, discussed the significance of synthetic chest X-ray images for COVID-19 detection and their potential in the field of medical imaging and diagnosis [9]. They generated COVID-19 chest X-ray images using an ACGAN model, a variation of GAN. To prevent overfitting of the model, they introduced label smoothing techniques. Using both the generated and original images, they trained a downstream classifier. They performed feature selection using the Harmony Search algorithm (HS) on feature vectors extracted from a CNN classifier based on the synthesized images. The results of this study showed that the CNN classifier trained based on the generated images achieved an accuracy of over 98%. Furthermore, while performing feature selection using the HS algorithm, they were able to maintain a classification accuracy of 100%, which indicates highly promising results.

ABDUL WAHEED et al. proposed CovidGAN by modifying the existing ACGAN model [10]. CovidGAN introduces an additional classifier to the generator and discriminator to classify the generated images as Covid-19 positive or negative. This enables CovidGAN to generate synthetic chest X-ray images for Covid-19 detection. The research results confirmed that using CovidGAN to generate synthetic data and adding it to the existing dataset improves the performance of CNN models. The CNN model trained on the synthetic data demonstrated an increased ability to detect COVID-19 in actual chest X-ray (CXR) images, with accuracy increasing from 85% to 95%. However, this study has limitations as it was conducted on a limited dataset, and further validation of its efficacy is required through more extensive datasets and experiments.

B. CT

Jacopo Lenkowicz et al. conducted a study on utilizing cGAN to generate artificial CT (Computed Tomography) images from MRI (Magnetic Resonance Imaging) [11]. This approach simplifies the complex CT scanning process for patients undergoing low-dose MR-guided radiation therapy by using artificial CT images. The researchers collected MRI images of lung cancer patients and used cGAN to generate artificial CT images. They evaluated the accuracy by comparing the generated artificial CT images with real CT images and reported that there were no significant differences between the artificial CT and real CT images. The permissible error ranges for the gamma passing rate were set at 2%/2mm and 3%/3mm. The accuracy of pure synthetic CT (sCT) was measured to be 95.5 ± 5.9% and 98.2 ± 4.1%, while the accuracy of hybrid sCT was measured to be 96.1 ± 5.1% and 98.5 ± 3.9%. These results quantitatively demonstrate that the generated artificial CT images exhibit a similar level of accuracy to real CT images.

Xiao Liang et al. conducted a study on overcoming the differences between CT (Computed Tomography) and CBCT (Cone-beam computed tomography) images and synthesizing CBCT images of comparable quality to CT images [12]. They employed CycleGAN for this purpose. In this study, the authors first analyzed the differences and issues between CBCT and CT images, including noise, artifacts, and inaccurate Hounsfield unit (HU) values. They proposed a technique to generate synthesized CT (sCT) images as a solution to these challenges. The CycleGAN model was used to transform CBCT images into CT-like images. Operating in an unsupervised learning manner, the model did not require precisely matched pairs of CT and CBCT images. Instead, CycleGAN learned the transformation function from CBCT to CT-like images and simultaneously learned the inverse mapping function from CT-like to CBCT images. Through various experiments, the proposed sCT generation technique demonstrated superior performance compared to other existing methods. For instance, the evaluation of the generated sCT images using CBCT and dpCT images of 20 patients to assess the consistency with treatment planning used in hospitals showed that sCT images generated using PGGAN exhibited the highest gamma passing rate, while those generated using CycleGAN exhibited the lowest gamma passing rate. These results validate the effectiveness of the proposed sCT generation technique as a method to synthesize CBCT images of comparable quality to CT images.

Vasant Kearne et al. propose an innovative method in the field of MR-to-CT image translation, referred to as "Attention-Aware CycleGAN" [13]. In contrast to traditional approaches, they perform image translation between CT and MR images without the need for paired data by using CycleGANs. CycleGANs combine adversarial loss and cycle consistency loss to maintain the consistency of image translation. Additionally, the authors introduce attention-aware discrimination and Variational Autoencoders (VAEs) to enhance the accuracy and depth of the model. Experimental results demonstrate the effectiveness of their approach compared to existing methods, emphasizing the advantages of MR-only treatment planning. This research introduces a novel approach to image translation in the medical field, presenting various potential applications. It is expected to address image translation challenges in the medical field from a new perspective and enhance diagnostic and treatment outcomes.

C. MRI

Isaac R. L. Xu et al. conducted a research with the goal of utilizing artificial intelligence technology in the medical field to generate MRI images, thereby saving costs and time in medical diagnosis and treatment [14]. In this study, the authors used 3T MRI image data collected from 50 patients for the first time. They performed image normalization, including resizing the images and removing non-brain regions. Then, they trained a GAN model using SinGAN. SinGAN generates a model capable of training on a single image to generate random samples. To evaluate the quality of the generated images, a comparison was made between the generated images and the real images. In the two quality control tests proposed by the authors, the group of experienced scientists showed an accuracy of 67%, the group with one year of experience showed an accuracy of 58%, and the group with no prior experience showed an accuracy of 50%.

Yawen Liu et al. conducted a study to evaluate the feasibility of fast image reconstruction in synthetic MRI using deep learning techniques and investigate the potential value of applying deep learning to quantitative magnetic resonance imaging (MRI) and weighted image calculations in a clinical setting [15]. The study obtained approval from the Medical Research Ethics Committee of Beijing Friendship Hospital, Capital Medical University, and obtained written consent from the participants. Using synthetic MRI data, the study trained a multi-channel U-Net-based deep learning architecture to generate quantitative maps and weighted images. The generated images provided an overall image quality similar to synthetic MR images and were able to generate whole-brain images in approximately 2 seconds. These results demonstrate the potential value of utilizing deep learning in quantitative MRI and weighted image calculations in clinical applications.

Siyeop Yoon et al. introduced an innovative technology in the field of cardiac MRI imaging with their Resolution Enhancement Generative Adversarial Neural Network (REGAIN) [16]. This model is based on GAN (Generative Adversarial Network) technology, a subset of deep learning. It enhances the resolution of MRI images, a crucial factor in the diagnosis and anatomical assessment of cardiac MRI images. The REGAIN model proposes an innovative approach that not only generates high-resolution images but also reduces acquisition time. These benefits improve the patient care process and enable researchers to obtain faster and more accurate images. Furthermore, this paper discusses how the REGAIN model was trained using retrospectively identified cine images and addresses the process of restoring the spatial resolution of cine images acquired using GRAPPA or CS techniques. The model evaluates the diagnostic quality and artifacts of the restored images, as well as the consistency for left ventricular function, volume, and strain. Experimental results demonstrate that this method provides higher resolution and enhances diagnostic quality compared to existing methods. Consequently, medical professionals can perform more accurate and detailed analyses, leading to more precise evaluations of patients' health. Additionally, the REGAIN model reduces image acquisition time and provides a patient-friendly healthcare process. This innovative technology is expected to play a significant role in various applications within the medical field, including early diagnosis and monitoring of cardiac diseases and anatomical research. As a result, it promises numerous benefits in patient care and medical research.

D. PET

Muhammad Sajjad et al. conducted a study utilizing PET images to improve the accuracy of Alzheimer's disease diagnosis [17]. In this study, a collected dataset of PET images was preprocessed and used as input for a DCGAN (Deep Convolutional Generative Adversarial Network) model. The DCGAN model generated synthetic synthesis of brain PET images based on the input data, which was combined with real PET image datasets to construct a training dataset. By training deep learning algorithms on this constructed dataset, the accuracy of Alzheimer's disease diagnosis was improved. The research results demonstrated the utility of deep learning algorithms utilizing the generated synthetic images in enhancing the accuracy of diagnosis. This study contributes to the direction of improving the accuracy of Alzheimer's disease diagnosis using PET images.

Mohammad Amin Abazari et al. proposed a novel framework for generating PET images of tumors and conducted research to enhance the accuracy and efficiency of PET image synthesis [18]. In this study, the authors presented a comprehensive spatio-temporal distribution model to simulate the uptake in two types of static and dynamic microvascular networks based on PET 18F-FDG (18F fluorodeoxyglucose). Subsequently, the DCGAN (Discriminative Convolutional Generative Adversarial Network) model was utilized, taking the 18F-FDG images as input, to generate images that resemble real PET samples. Radiologists then compared the synthesized 18F-FDG PET images with real images to distinguish between genuine and generated images and evaluate the quality of each image. Furthermore, the authors emphasized the need for quality assessment metrics (such as SSIM, PSNR, Inception Score) and mentioned that comparing the evaluations with human judgments proved to be helpful. In conclusion, this study demonstrates the potential of effectively synthesizing PET images used in nuclear medicine imaging by combining bio-mathematical modeling and machine learning techniques.

Shijie Chen et al. introduce a novel GAN architecture called DAEGAN to address the crucial issue of improving the quality of PET images acquired through low-dose radioactive injection [19]. PET imaging plays a significant role in the medical field, and the accuracy of image quality impacts disease diagnosis and patient management. The DAEGAN architecture is designed with a focus on high-quality restoration of PET images, utilizing a dual-domain attention-enhanced encoder-decoder. This paper mathematically models the DAEGAN architecture, providing a detailed explanation of its internal workings and technical details regarding network architecture and loss functions. In the experimental section, the performance of the DAEGAN architecture is evaluated using real PET datasets, and the results are analyzed in comparison to existing methods. The experimental results demonstrate that the DAEGAN architecture outperforms existing methods in terms of image quality improvement, making a significant contribution to the field of medical imaging. This research introduces an innovative approach to addressing image quality issues caused by low-dose radioactive injections, garnering attention as an important study for enhancing image quality in the medical field.

III. DISCUSSION

This study conducted an investigation into the current trends and advancements of generative AI in the domain of radiology imaging. It covered various types of radiology images, including CT, MRI, X-ray, and PET, emphasizing their potential applications in the medical field. By integrating generative AI techniques with radiology imaging, the study highlighted the potential benefits of streamlining medical processes and enhancing diagnostic accuracy.

However, it is important to note that most of the research is based on limited datasets. This poses challenges to the generalization and robustness of the models. Therefore, there is a need for the construction of more diverse and comprehensive datasets to support research and development. In particular, the quality of the data used to train AI algorithms is crucial, as issues such as sample selection bias can arise [20]. Improving the performance of generative AI models on small datasets is a key challenge in the medical field to generate more reliable results.

Furthermore, it is crucial to consider the data format when determining the research direction. The use of grayscale images has the advantage of reducing dimensions and sizes compared to RGB images. The results regarding this can be observed in Table 1 [21], where grayscale X-ray, CT, and MRI data show at least 80% or higher results. On the other hand, for RGB PET data, especially in the study by Mohammad Amin Abazari et al., evaluation metrics such as SSIM and PSNR are provided, but it is mentioned that human evaluation is superior to these metrics. This suggests that grayscale data provides better results than RGB data, so careful consideration is required when generating RGB data.

Moreover, ethical considerations regarding Generative AI techniques for radiology imaging should not be overlooked [22]. These aspects need to be carefully considered in future research and development processes. It is highly important to consider ethical aspects and prioritize privacy protection.

TABLE 1. RADIOLOGY IMAGE-SPECIFIC GENERATIVE AI SUMMARY TABLE.

Types	Author	Model Used	Evaluation Method	Result
X-Ray	Yash Karbhari et al.	ACGAN + HS algorithm	Accuracy(%)	100.0 ± 0.00
	ABDUL WAHEED et al.	COVID-GAN	Accuracy(%)	increased by 10% (85% to 95%)
CT	Jacopo Lenkowicz et al.	cGAN	Gamma Passing Rate	- Pure sCT: 95.5 ± 5.9%, 98.2 ± 4.1% - Hybrid sCT: 96.1 ± 5.1%, 98.5 ± 3.9%
	Xiao Liang et al.	CycleGAN	MAE (Mean Absolute Error)	decreased by about 4 HU (69.29 HU to 29.85 HU, data analysis based on standard of head-and-neck cancer patient data)
	Vasant Kearne et al.	A- CycleGAN	PSNR(Mean)	- U-net: 54.67 - GAN: 58.81 - CycleGAN: 61.58 - A-CycleGAN: 62.35
			MAE(Mean)	- U-net: 26.12 - GAN: 23.32 - CycleGAN: 21.34 - A-CycleGAN: 19.61
			SSIM(Mean)	- U-net: 0.672 - GAN: 0.712 - CycleGAN: 0.742 - A-CycleGAN: 0.778
MRI	Issac R. L. Xu et al.	SinGAN	Wilcoxon signed ranked test	- Group of experienced scientists: 67% accuracy - Less Experienced Group: Less Accuracy (about 50%)
	Yawen Liu et al.	Multichannel U-net based Deep Learning Architecture	MSE	- T1Map: 0.0078 - T2Map: 0.0093 - PDMap: 0.0032
			MAE	- T1Map: 0.0292 - T2Map: 0.0292 - PDMap: 0.0291
			MAPE	- T1Map: 0.0575 - T2Map: 0.1113 - PDMap: 0.0768
	Siyeop Yoon et al.	REGAIN	breath-hold ECG-gated segmented cine, free-breathing real-time cine, etc.	GRAPPA and REGAIN show no significant difference in various evaluation metrics.
PET	Muhammad Sajjad et al.	DCGAN	VCG16	Overall accuracy: 0.72%
	Mohammad Amin Abazari et al.	18F-FDG PET + DCGAN	SSIM	0.72
			PSNR	28.53
	Shijie Chen et al.	DAEGAN	PSNR↑, RMSE↓, SSIM↑ (SAPET/ ANDI)	- Low-Dose: 35.47 ± 6.74/27.13 ± 0.06, 5.489 ± 3.87/11.21 ± 0.0.08, 0.887 ± 0.13/0.534 ± 0.01 - CPCE-2D: 36.48 ± 5.68/37.28 ± 0.60, 4.680 ± 3.00// 3.494 ± 0.24, 0.894 ± 0.09/0.960 ± 0.01 - REDCNN: 36.66 ± 5.07/35.41 ± 0.35, 4.491 ± 3.12/4.324 ± 0.17, 0.844 ± 0.08/0.958 ± 0.01 - PT-WGAN: 36.89 ± 5.24/37.84 ± 0.69, 4.493 ± 3.71/3.280 ± 0.26, 0.894 ± 0.10/0.964 ± 0.01 - Proposed: 37.65 ± 6.04/ 38.45 ± 0.83, 4.223 ± 3.06/ 3.061 ± 0.29, 0.920 ± 0.09// 0.971 ± 0.01

Therefore, future research should aim to construct more diverse and comprehensive datasets while pursuing the generalization and performance improvement of Generative AI models. Thorough consideration of ethical aspects and privacy protection is also necessary. Through these efforts and considerations, the potential of utilizing Generative AI in the field of radiology imaging can be maximized.

IV. CONCLUSION

This study concludes that the advancement of Generative AI based on radiology imaging holds significant potential in the field of healthcare. The integration of radiology imaging and Generative AI technology can contribute to improving the efficiency of medical processes and enhancing diagnostic accuracy.

Therefore, future research should focus on increasing the diversity and scale of datasets while aiming for the generalization and performance improvement of Generative AI models. Additionally, thorough consideration of ethical aspects and privacy protection is necessary. Through these efforts and considerations, the potential of utilizing Generative AI in the field of radiology imaging can be maximized.

V. ACKNOWLEDGMENT

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korean government (MSIT). Specifically, it was supported by the grant No.2020-0-01343, Artificial Intelligence Convergence Research Center (Hanyang

University ERICA), and the grant No.RS-2022-00155885, Artificial Intelligence Convergence Innovation Human Resources Development (Hanyang University ERICA).

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