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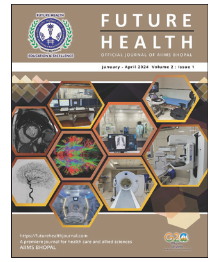

Review Article

Harnessing generative AI: Transformative applications in medical imaging and beyond

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ABSTRACT

Generative AI is an expanding domain that employs machine learning models to generate novel data that closely mimic pre existing data. ChatGPT and DALL-E can be customized for specific applications and are expected to transform healthcare, education, and communication. Generative Adversarial Networks (GANs) that can generate synthetic medical images closely mimicking actual patient data may substantially enhance machine learning model training datasets. They also translate medical images from one modality to another, improve medical imaging resolution, reduce radiation exposure, and boost image quality and detail.

Despite their challenges, GANs have great potential in the field of medical imaging. The key obstacles are the need for Graphic Processing Units (GPUs) and computing resources to train GANs and the lack of established standards for generating synthetic images. Incorrectly labeled data for training other machine learning models can reduce performance, making ground-truth data labeling for healthcare AI more difficult.

Generative AI is revolutionizing healthcare imaging, simplifying diagnosis, and propelling healthcare research and practice to new frontiers. Ensuring the reliability and safety of generated images in medical applications requires addressing ethical considerations and validating data.

Keywords: Generative AI, GANs, Chat GPT, Image synthesis

INTRODUCTION

Generative AI leverages machine learning models to create new data that resemble existing data. This form of AI is designed to generate new data like images, music, text, and video.[1] Generative AI uses foundation models that can multitask and perform summarization, question and answer, classification, and more without customization. With minimal training and sample data, basic models can be tailored for specific use cases. Notable GenAI models include ChatGPT (generative pretrained transformer), DALL-E, etc. The term "GPT" encompasses Large Language Models (LLMs) that employ deep learning methods to undergo extensive training using enormous amounts of data. ChatGPT is a conversation-optimized language paradigm. It generates responses that resemble human-like speech by using its extensive information and understanding. ChatGPT harnesses the power of generative AI, a form of artificial intelligence that can produce text and creative content resembling human output. It can also gather and analyze data from many sources.[2,3] Merging the most effective aspects of different generative models allows one to build more robust models. One can create more powerful models by combining the best features of each generative model. Generative AI, especially Generative Adversarial Networks (GANs), improves medical imaging by offering innovative solutions. This advanced AI is expected to transform society, lives, jobs, education, and communications.[4]

DISCUSSION

Due to their data-generating ability, GANs are a trendy topic in artificial intelligence research. The main functions of generative AI in medical imaging are listed below:

Image Synthesis and Augmenting Data

GANs have the ability to produce artificial medical images that closely resemble actual patient data. This is especially advantageous when working with restricted datasets since it aids in augmenting training sets for machine learning models.[5,6] GANs involve two adversarial networks: the generator generates new and authentic-looking data by learning the data distribution from training samples, while the discriminator reliably classifies images as real or fake using binary classification. In successive iterations, the discriminator is updated to better distinguish between real images and those generated by the generator. The generator, in turn, is updated based on how well the generated images deceived the discriminator. GAN training does not restrict generator architecture. Thus, medical image augmentation approaches based on GANs provide significant research potential.[7] The two modules improve alternately through iterative training and the interplay between these opposing networks enhances the overall performance of the GANs.[8] It generates many samples to train robust models. Skanadarani Y developed a GAN to create authentic-looking T1-weighted brain MRIs.[2] F Faisal created false data while protecting patient privacy.[9] de Moura suggested that data augmentation considerably increases the diversity of data available for training models, reducing overfitting and enhancing model resilience. This is particularly relevant with the shortage of verified Covid-19 cases.[10] GANs may create artificial histopathology images to train deep-learning models for cancer detection and analysis apart from education and research purposes.[11]

Image-to-Image Translation

GANs transform medical images between modalities, which aids multimodal imaging and image comprehension. MedGAN performs PET-CT translation, MR motion artifact correction, and PET image denoising without modification. Radiologists' perceptions and quantitative evaluations show that MedGAN outperforms alternative translating systems.[12] Sorin V generated MRI images from CT scans for improved soft tissue clarity.[13] Ali H demonstrated the enhancement of image clarity while reducing radiation exposure by the conversion of standard dose to low dose.[14]

Super-Resolution Imaging

Medical image analysis requires high image resolution. High-resolution images with complex features are essential for accurate diagnosis. Medical imaging requires expensive equipment and skilled staff to obtain high-resolution images. Super-resolution techniques can improve low-resolution images captured by current technology using deep learning algorithms.[15,16] Zhang K evinced that generative AI improves medical image quality and detail, increasing resolution and precision for more accurate diagnosis.[17]

Artifact Removal

Radiation can harm genes and cause cancer. This raises worries regarding patient radiation exposure. Thus, the As Low as Reasonably Achievable (ALARA) principle—keeping radiation exposure as low as reasonably achievable—has become well-known. Reduced radiation dose causes more interference and irregularities in the reconstructed image, lowering diagnostic quality. Generative AI removes image noise and artifacts while preserving architecture and removing erroneous lesions, increasing signal to noise ratio, hence improving image quality.[18]

Creating Realistic Simulation Phantoms

Generative AI (GAI) can create realistic 3D medical phantoms of various structures and diseases. It helps create realistic datasets for medical imaging algorithm training and testing. Various imaging modalities are tested in virtual clinical trials with different patient populations.[19,20]

CHALLENGES

The requirement for graphics processing units and substantial computing resources to train GANs presents the primary obstacle. An additional significant challenge is the absence of quality criteria for creating synthetic images. Improperly labeled data used to train other machine learning models can impair their performance, adding to the already substantial challenge of accurate and trustworthy ground-truth data labeling for AI in healthcare.

The scientific study requires patient agreement for medical image compilation. The status of generated photographs or datasets derived from them as original or fresh data makes patient consent unclear. The legality of newly collected data is unclear. Consent from patients is necessary for the scientific study's medical image collection. Patient permission is not clearly defined because datasets created from generated images are not considered new or original data. Newly acquired data have an uncertain legal status.[21]

Medical images, unlike others, have intricate structures and can provide pathogenic information. In the domain of medical imaging, the analysis of an image can have a significant impact on the patient's life. Therefore, certain technologies that are effective in other fields for comparable reasons may not be suitable for this specific medical profession. Furthermore, medical imaging categories differ greatly. More medical prior knowledge can be included in the GAN design, resulting in precise network designs and loss functions.[21,22]

CONCLUSION

New possibilities in medical imaging are emerging, thanks to Generative AI. These innovations improve healthcare imaging, make diagnosis easier, and push the boundaries of healthcare research and practice forward. Addressing ethical concerns and validating data for medical applications is crucial for ensuring the dependability and safety of generated images.

Ethical approval

Institutional Review Board approval is not required.

Declaration of patient consent

Patient's consent is not required as patient's identity is not disclosed or compromised.

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Conflicts of interest

There are no conflicts of interest

Use of artificial intelligence (AI)-assisted technology for manuscript preparation

The authors confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript and no images were manipulated using AI.

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