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The Future Role of Generative Artificial Intelligence (AI) in Medicine

Murat Türk,[1] Engin Zeydan,[2] Suayb S. Arslan,[3] Yekta Türk[4]

[1]Department of Allergy and Clinical Immunology, Erciyes University Faculty of Medicine, Kayseri, Türkiye
[2]Communication Networks Division, Centre Tecnològic de Telecomunicacions de Catalunya (CTTC), Barcelona, Spain
[3]Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA
[4]Independent Researcher, Ankara, Türkiye

Generative Artificial Intelligence (GenAI) is revolutionizing medicine by autonomously creating content such as images, text, and audio files. This transformative force addresses longstanding challenges in healthcare and offers innovative solutions across research, diagnosis, treatment, and patient care. This paper focuses on deep generative models within GenAI and categorizes them based on architecture and applications. We highlight the potential applications of various Generative AI models in medicine, emphasizing their role in transforming healthcare (Fig. 1).

AUTOENCODER-BASED MODELS

Variational Autoencoders (VAEs)

Applications: VAEs are powerful tools for representational learning that capture intricate patterns in genetic makeup, lifestyle, and medical history. They are used in multi-omics analysis and aid in disease diagnosis, drug discovery, and the development of personalized therapeutic strategies. VAEs use encoded latent spaces to create personalized treatment plans, transitioning from the traditional one-size-fits-all model to more targeted healthcare solutions.[1] Additionally, they excel in generating synthetic data and preserving patient privacy, contributing to mental health support by developing virtual assistants for psychological care.

Adversarial Autoencoders (AAEs)

Applications: AAEs combine autoencoder principles with adversarial training to generate samples while preserving the encoded representations.[2] Key applications of AAEs in medicine include image generation, representation learning, drug development (AAEs are particularly useful for exploring the chemical space in a structured way), and medical text generation (where they can generate detailed medical reports and summaries based on patient data and clinical findings). The adversarial training aspect helps create more realistic and accurate medical texts, making AAEs suitable for automating the process of medical documentation and increasing the efficiency of healthcare providers.

ADVERSARIAL MODELS

Generative Adversarial Networks (GANs)

Applications: GANs have exceptional capabilities in generating realistic and high-resolution medical images, addressing challenges in scenarios where acquiring large datasets for train-

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Address for correspondence:
Murat Türk.
Department of Allergy and Clinical Immunology, Erciyes University Faculty of Medicine, Kayseri, Türkiye
Phone: +90 352 207 66 66 /21186
E-mail: mrttrk@gmail.com

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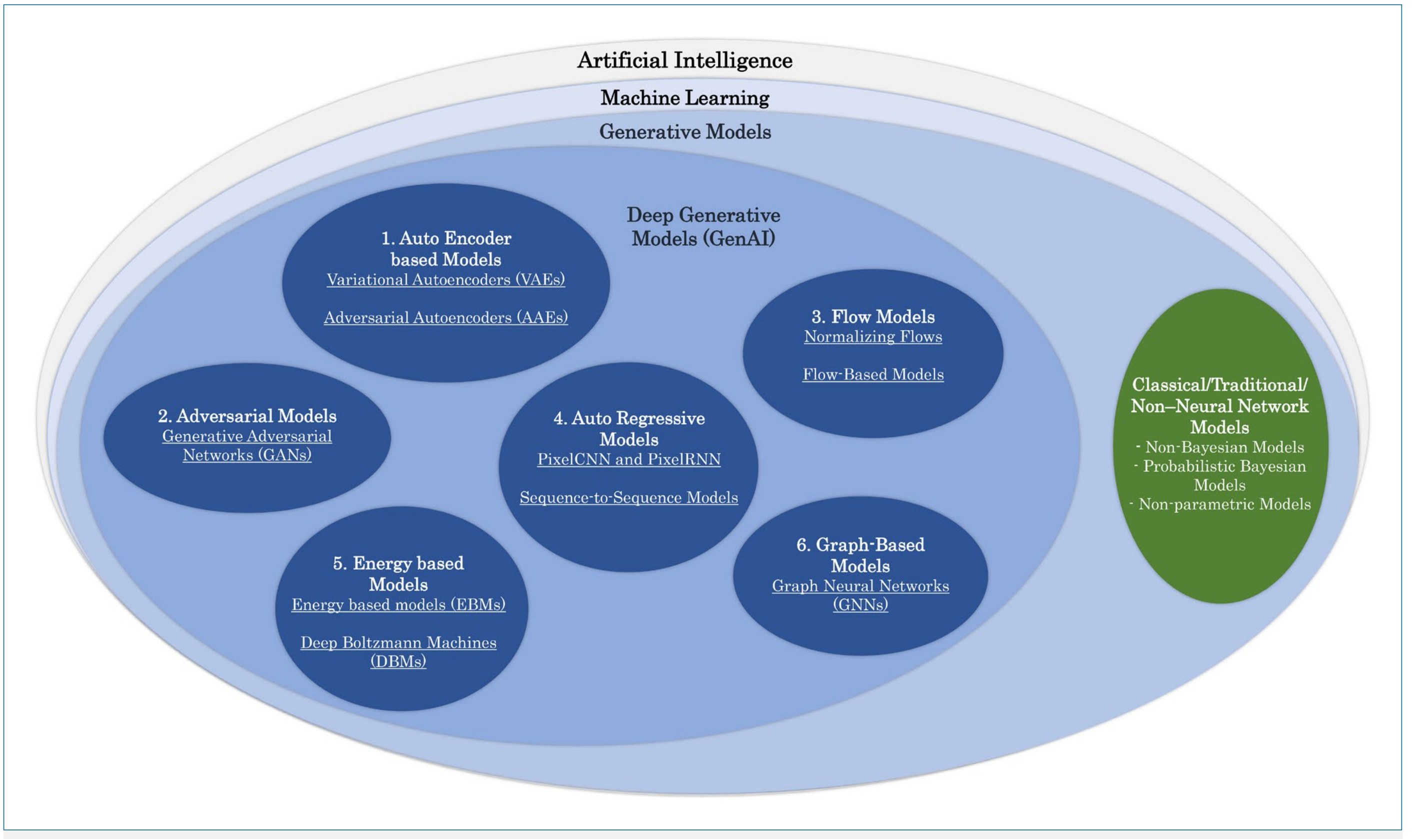

Figure 1. Deep generative models (GenAI) are a subgroup of generative models, distinct from classical, traditional, or non-neural network models. The potential applications of various GenAI models in medicine can be categorized under six major subtypes, based on their architecture and applications.

ing are scarce.[3] They enhance image-to-image translation, simulation-based training, disease progression modeling, augmented reality in surgery, and rehabilitation/prosthetics. GANs play a crucial role in reducing risks associated with real-life training scenarios, thus enhancing patient safety.

GANs simulate disease progression using historical patient data and provide valuable insights for clinicians. They aid in understanding how diseases evolve over time and improve overall management and treatment strategies. In augmented reality for surgery, GANs excel at creating synthetic information overlays due to their ability to generate realistic and diverse patterns. The synthetic overlays generated by GANs enhance the visual information available to surgeons in real time, aiding in more informed and accurate decision-making in complex surgical contexts. Additionally, in the field of rehabilitation and prosthetics, GANs contribute to the development of customized assistive devices with their ability to generate realistic and diverse patterns, ultimately improving the mobility and quality of life for people with physical disabilities.

FLOW MODELS

Normalizing Flows

Applications: Normalizing flows utilize invertible transformations for high-dimensional data generation, density estimation, and medical image analysis.[4] Normalizing flows are particularly effective in generating high-resolution images from low-quality data. They improve the precision of medical scans and aid in the detection and diagnosis of diseases such as cancer, bone fractures, and neurological disorders.

Flow-Based Models (e.g., Real NVP, Glow)

Applications: Models such as Real NVP and Glow utilize invertible transformations for generative modeling and tractable probability.[5] Flow-based models contribute to the generation of synthetic data while preserving data privacy. They effectively help train AI algorithms using large amounts of data.

AUTO REGRESSIVE MODELS

PixelCNN and PixelRNN

Applications: These models improve the analysis of medical imaging by generating high-resolution images from low-quality inputs.[6] Their sequential generation capabilities meet the specific needs of medical image analysis. This technology can improve the accuracy of disease detection and diagnosis in medical imaging.

Sequence-to-Sequence Models (RNNs with Attention Mechanisms)

Applications: RNNs with attention mechanisms significantly enhance medical text generation and play a crucial role in producing detailed medical reports and summaries.[7] These models are valuable for mental health support, simulating human-like conversations. Additionally, they serve as a tool for diagnosing complex clinical cases.

ENERGY-BASED MODELS (EBMS)

EBMs

Applications: EBMs are significant in predictive analytics within medicine, analyzing vast amounts of patient data to predict disease outbreaks, patient readmissions, and other critical events. This analysis aids healthcare facilities in better preparation and resource allocation.[8]

Deep Boltzmann Machines (DBMs)

Applications: DBMs are effective in generating synthetic data, especially in scenarios where data privacy is a concern, such as healthcare.[9] They capture complex data relationships, making them suitable for various tasks.

GRAPH-BASED MODELS

Graph Neural Networks (GNNs)

Applications: GNNs process graphically structured data, making them ideal for analyzing movement patterns and medical histories.[10] They enhance personalized aids in rehabilitation and prosthetics and improve the quality of life for individuals with physical disabilities.

The application of generative AI in medicine is a rapidly evolving field with immense potential to transform various aspects of healthcare. From improving medical imaging and drug discovery to personalizing treatment plans and advancing medical education, generative AI is reshaping the medical landscape. As research on the potential applications of GenAI in clinical settings continues, clinicians must be aware of the associated risks. Ethical considerations and regulatory frameworks are essential for integrating GenAI into medicine. The responsible development and use of these technologies require careful consideration of issues such as privacy, bias, and the interpretability of AI-generated results. Balancing innovation and ethical considerations is key to ensuring that the use of generative AI in healthcare is both responsible and beneficial. It is critical for all stakeholders, including healthcare professionals, patients, medical researchers, pharmaceutical companies, healthcare institutions, AI developers and engineers, health authorities, ethics committees, legal experts, insurance companies and payers, medical schools and educational institutions, and the general public to work together, address ethical concerns, and develop robust regulatory frameworks. This collaborative effort is necessary to realize the full potential of generative AI in improving global healthcare delivery.

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