VignetteGen: Leveraging Large Language Models and Generative Adversarial Networks for Holistic Synthetic Medical Scenarios with Imaging

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1 Background

Synthetic data for clinicopathologic deep learning has been extensively explored due to the limited datasets researchers can access, often as a result of privacy concerns and limitations, bias, and sparsity for underrepresented diseases (Pantanowitz et al., 2024), and synthetic data also has potential for low-risk, feedback-rich simulated learning environments for medical students in training (Rashidi et al., 2025). Generative adversarial networks (GANs) have achieved remarkable results for creating self-consistent synthetic medical imaging data that can even be tailored to specific outcomes (Gu et al., 2022), and large language models (LLMs) have shown promising results for generating patient scenarios indistinguishable from human-generated scenarios (Smith et al., 2025). However, multimodal models seeking to implement paired textual and image features face a unique challenge where data is even more limited given the need for the two to correspond, and researchers must train on data for scenarios (history of present illness, family/social history, etc.) and imaging (whole slide images, x-rays, etc.) that are not always paired. Current generative learning tools for medical students also lack this critical connection between clinical context and medical imaging, making holistic training difficult.

2 Proposed Solution

This study will explore a novel framework that uses an LLM to generate artificial patient scenarios and clinical history, then feeds into a GAN to generate relevant medical imaging tied to the specific scenario. We propose the exploitation of a visual encoder at training time as seen in vision-language models (VLMs) to enable the LLM to receive the same image data as the GAN for the best consistency between the text output and the medical images. To the best of our knowledge, this will be the first work to generate holistic synthetic medical scenarios that include both clinical data and medical imaging. The results of this paper will also offer generated scenarios with relevant medical imaging data to medical students seeking a low-risk, feedback-rich automated educational tool without relying on constant feedback and large time commitments from attending physicians.

References

Jinjin Gu, Xinlei Wang, Chenang Li, Junhua Zhao, Weijin Fu, Gaoqi Liang, and Jing Qiu. 2022. Ai-enabled image fraud in scientific publications. *Patterns*, 3(7):100511.

Joshua Pantanowitz, Christopher D. Manko, Liron Pantanowitz, and Hooman H. Rashidi. 2024. Synthetic data and its utility in pathology and laboratory medicine. *Laboratory Investigation*, 104(8):102095.

Hooman H. Rashidi, Joshua Pantanowitz, Alireza Chamanzar, Brandon Fennell, Yanshan Wang, Rama R. Gullapalli, Ahmad Tafti, Mustafa Deebajah, Samer Albahra, Eric Glassy, Matthew G. Hanna, and Liron Pantanowitz. 2025. Generative artificial intelligence in pathology and medicine: A deeper dive. *Modern Pathology*, 38(4):100687.

Gordon Smith, Katalina Pho, Ka Yan Harrison, Steven Kass, and Thomas Reichherzer. 2025. Enhancing medical training with ai-driven scenario generation. In *2025 IEEE International Conference on Digital Health (ICDH)*, pages 11–20.