Fake It Till You Make It: Synthetic Generation of Pediatric Liver Ultrasound Images using Generative AI models

Phuc Ngoc Thien Nguyen[1], Smruti Deoghare[2], Andrew T. Trout[3], Jonathan R. Dillman[3], Vasundhara Acharya[4], V. B. Surya Prasath[2,5]

[1]Department of Biomedical Engineering, University of Cincinnati, [2] Division of Biomedical Informatics, [3]Division of Radiology, CCHMC, [3]Department of Electrical Engineering and Computer Science, Rensselaer Polytechnic Institute, NY, [5]Departments of Pediatrics, Electrical Engineering and Computer Science, University of Cincinnati

INTRODUCTION

- Artificial intelligence (AI) has experienced extensive and successful applications in the field of healthcare due to advancements in deep learning (DL) and the availability of high-quality biomedical datasets.
- Despite ultrasound (US) being a common imaging modality used as a first step for various diagnoses, identifying a large enough dataset sufficient to train DL models remains a challenge.
- With increasing liver related diseases in pediatric population, but limited by the number of available images, we propose using "Generative Adversarial Networks" (GANs) to create synthetic US pediatric liver images with high accuracy. These would make the extant dataset more robust and offer a better input for training the "data greedy" AI models.

OBJECTIVES

1. Generate synthetic pediatric liver ultrasound (US) images using GANs.
2. Compare the performance of different GAN model frameworks and identify the top performing model.
3. Evaluate the ability of GANs to augment pediatric liver stiffness classification from US images based on shear wave elastography (SWE) thresholds.

MATERIALS AND METHODS

The pediatric live ultrasound (US) dataset included HIPAA-complaint de-identified 2675 images from 880 patients obtained in the Division of Radiology, CCHMC. These images - longitudinal/transverse - were preprocessed to eliminate visual noise and other artifacts. We next compared different types of generative adversarial networks (GANs) - conditional GAN (cGAN), deep convolutional GAN (DCGAN) [1], Wasserstein GAN with gradient penalty [2] (WGAN-GP) and progressive GAN [3].

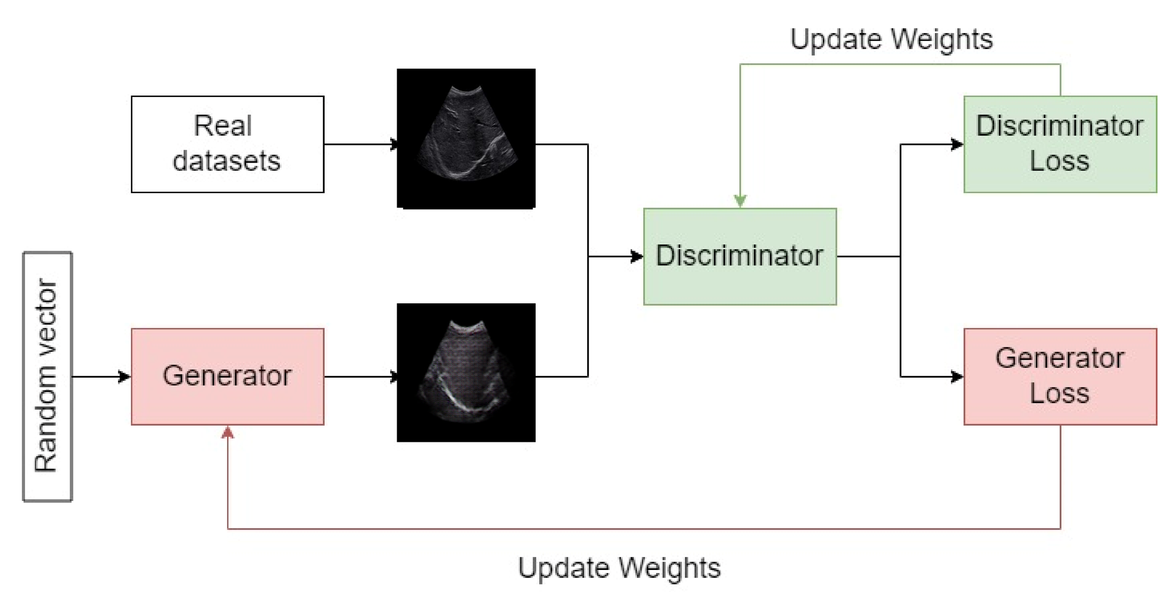

Fig. 1: General framework of generative adversarial networks (GANs)

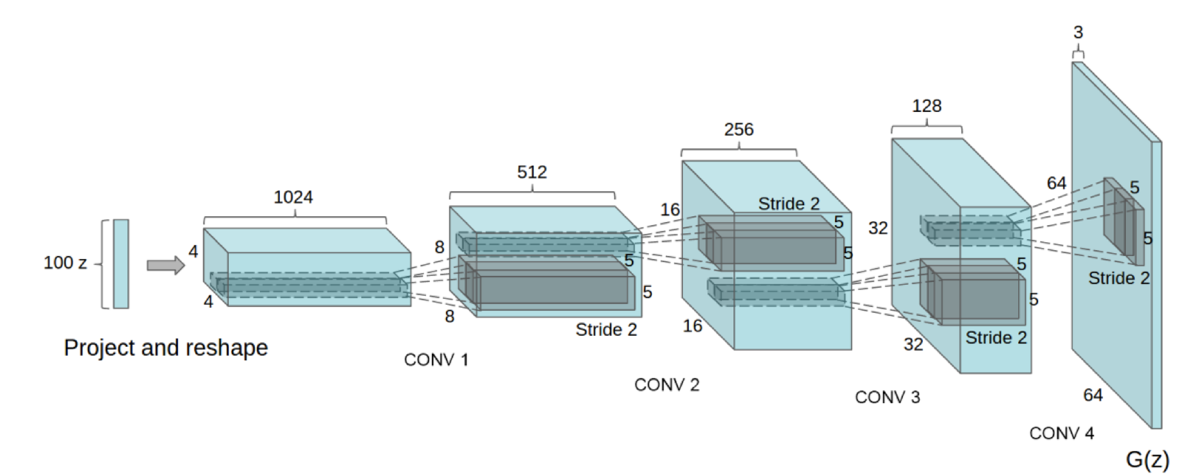

Fig. 2: Deep convolutional GAN (DCGAN) [1] framework

EXPERIMENTAL RESULTS

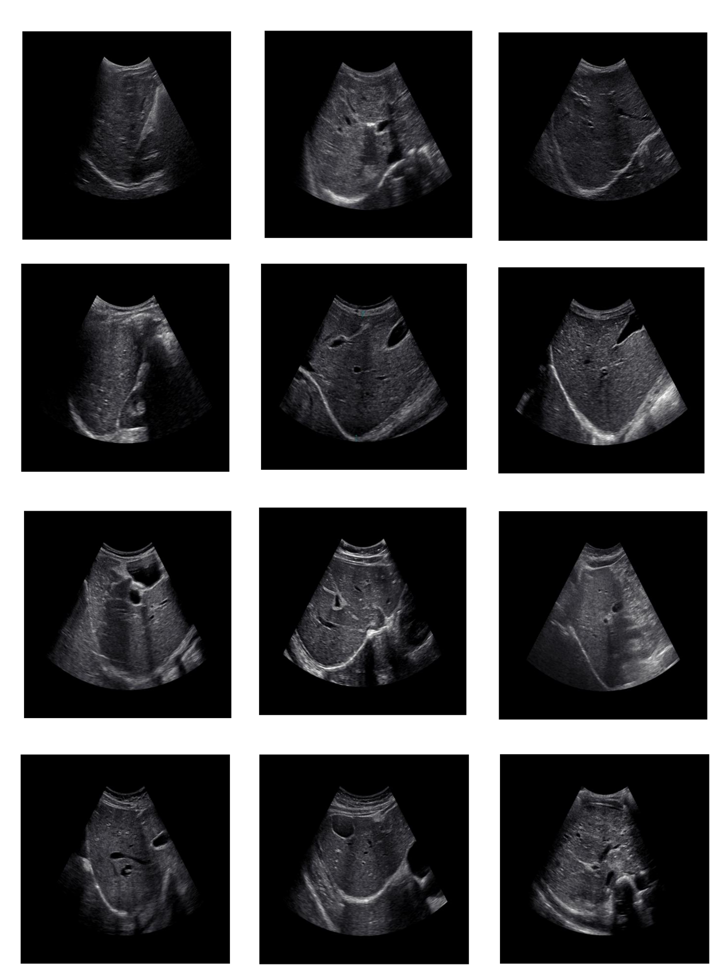

Fig. 3: Real US images extracted from dataset

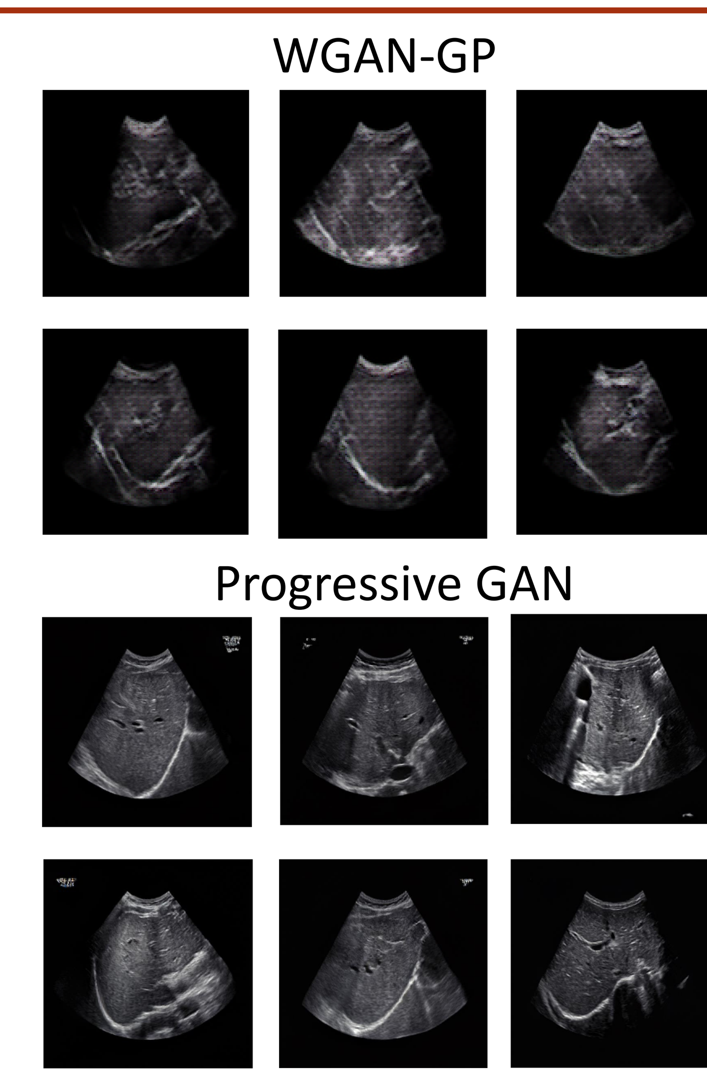

Fig. 4: Synthetic US images generated from GANs

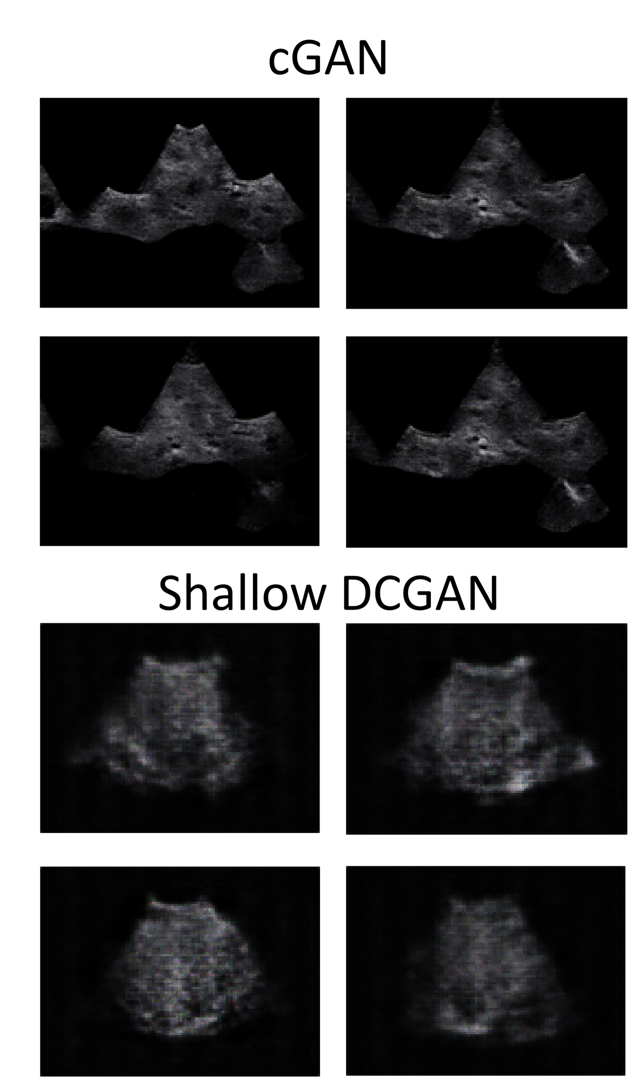

Fig. 5: Intermediate failure cases of synthetic US images generated by GANs

CURRENT WORK

- Experiment with other GAN models in the literature and perform comprehensive model performance comparison.
- Created an easy-to-use graphical user interface (GUI) that allows experts to identify the real US images from the synthetic generated by GAN models.
- Expand GAN with US modality specific constraints, for e.g., SpeckleGAN [4], domain specific speckle pattern layer to simulate US images.
- Augmentation of GAN generated synthetic US shear wave elastography (SWE) images in training data for pediatric liver stiffness prediction with deep convolutional neural network (CNN) model-based classification.

REFERENCES

1. A. Radford, Alec, L. Metz, S. Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv:1511.06434*, 2015.
2. I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, A. C. Courville. Improved training of wasserstein GANs. NeurIPS, 2017.
3. T. Karras, S. Laine, T. Aila. A style-based generator architecture for generative adversarial networks. *IEEE TPAMI*, 2021.
4. L. Bargsten A. Schlaefer A. SpeckleGAN: A generative adversarial network with an adaptive speckle layer to augment limited training data for ultrasound image processing. IJCARS, 2020.

ACKNOWLEDGEMENTS

The authors would like to thank Samjhana Thapaliya, Leah Gilligan, Division of Radiology, CCHMC for their help in the collection and curation of the in-house dataset, and the BMI Research IT, CCHMC for providing technical assistance in using the NVIDIA A100 GPUs/Cluster. Funding by ARC, CCRF, CCHMC.

www.prasathlab.com @prasathLab

Cincinnati Children's

nguye6tp@mail.uc.edu