GAN–based Synthesis of Contrast-Enhanced Hepatobiliary Phase Liver MRI without Primovist

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Abstract

Contrast-enhanced magnetic resonance imaging (CEMRI) plays a crucial role in diagnosing liver tumors. However, the use of gadolinium-based contrast agents, such as Primovist, presents challenges including risks to patient health, high costs, and prolonged imaging processes. Studies such as Lyu et al. (2023) have explored alternatives to reduce dependency on these agents, showcasing the potential of deep learning techniques [1]. This report details the development of a GAN-based approach for generating contrast-enhanced-like hepatobiliary phase liver MRI images from non-contrast-enhanced MRI (NCEMRI) scans. By leveraging methodologies outlined by Goodfellow et al. (2014) [2]and Isola et al. (2017) [3], this technique eliminates the need for contrast agents like Primovist, improving liver cancer diagnosis efficiency and accessibility while ensuring diagnostic quality comparable to traditional CEMRI.

CEMRI has historically been indispensable in identifying liver tumors, as supported by Jayachandran et al. (2021) [4]. However, reliance on gadolinium-based agents introduces risks, particularly for patients with renal impairments. Our novel approach, leveraging GANs, as highlighted in foundational works by Goodfellow et al. (2014) [2], showcases how synthetic enhancement can provide a safe alternative while maintaining diagnostic utility. The proposed method incorporates advanced training strategies and comprehensive validation processes to ensure clinical applicability. Results indicate that GANs can deliver diagnostic-quality synthetic images, paving the way for broader adoption in medical imaging workflows.

Assentation of Teamwork

Each team member contributed significantly to this project. Ruizhe Tang focused on GAN model architecture design and implementation, including developing the residual block structure for enhanced feature retention. Yeping Li handled data preprocessing and evaluation metrics, ensuring the dataset met quality standards through augmentation and alignment techniques. Kaiwen Zhu performed rigorous testing, validation, and documentation, ensuring the results aligned with clinical requirements and drafting comprehensive reports. Collaborative discussions were held weekly to ensure that individual contributions were aligned with the overarching project goals.

1 Introduction

The hepatobiliary phase MRI is a critical imaging modality for assessing liver function and identifying lesions, particularly in hepatocellular carcinoma (HCC) and other liver diseases. The importance of this imaging phase has been emphasized in recent studies, such as Lyu et al. (2023), where non-invasive imaging techniques are developed to reduce reliance on contrast agents [1]. However, the use of gadolinium-based agents like Primovist poses risks, particularly for patients with impaired renal function, and adds to the cost and complexity of imaging workflows [4]. Recent advancements in deep learning, especially Generative Adversarial Networks (GANs), have shown potential for synthesizing high-quality contrast-enhanced images from non-contrast inputs. This project aims to develop a GAN-based framework specifically tailored for hepatobiliary phase liver MRI, potentially revolutionizing diagnostic workflows by eliminating the need for contrast agents like Primovist.

The hepatobiliary phase is uniquely suited for synthetic image generation due to its reliance on contrast differences in bile excretion and liver tissue. Studies such as Hu et al. (2021) have shown that advanced GAN architectures can effectively replicate complex imaging phases by capturing subtle anatomical and functional details [5]. By replicating these contrast mechanisms through GANs, the need for invasive contrast injections can be eliminated. This aligns with broader healthcare trends emphasizing non-invasive, cost-effective, and efficient diagnostic tools [6].

2 Preliminaries and Problem Formulation

Problem Statement:

The goal is to synthesize hepatobiliary phase contrast-enhanced liver MRI images from NCEMRI scans using GANs.

Specific Dataset Choice:

We utilized a private dataset containing paired NCEMRI and Primovist-enhanced hepatobiliary phase MRI images. The dataset was curated to focus on liver function assessment, lesion detection, and anatomical accuracy. Images were obtained from multiple clinical sources, ensuring diversity in patient demographics and scanner settings. Preprocessing steps included spatial alignment to account for motion artifacts, intensity normalization for consistent contrast, and cropping to isolate the liver region.

Key Concepts:

Hepatobiliary Phase Imaging:

This phase highlights the liver's function through biliary excretion of contrast agents. Synthetic generation of this phase requires accurately replicating these functional and anatomical features without the use of gadolinium.

Generative Adversarial Networks (GANs):

GANs consist of a generator and discriminator working in tandem to create realistic outputs while differentiating them from actual data. For this project, the generator focuses on enhancing the liver's contrast and texture, while the discriminator ensures clinical realism.

Evaluation Metrics:

Metrics such as Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Normalized Mean Absolute Error (NMAE) are used to assess the fidelity and diagnostic relevance of the synthetic images.

3 Solution via Deep Learning

Dataset:

A curated dataset containing paired NCEMRI and hepatobiliary phase CEMRI images was utilized. Preprocessing included normalization of intensity values to standardize contrast, alignment to correct motion artifacts, and cropping to emphasize liver regions. Data augmentation techniques like rotations, flips, and intensity adjustments were applied to enhance model robustness.

Model Architecture:

1. **Generator:** A convolutional neural network with down sampling, residual blocks, and up sampling layers designed to capture and replicate the hepatobiliary phase's unique contrast characteristics. Residual blocks ensured retention of critical anatomical details, especially in regions of interest such as bile ducts and liver lesions.
2. **Discriminator:** A dual-discriminator setup was implemented:
    - **Local Patch Discriminator:** Focuses on fine details such as bile ducts and lesion boundaries.
    - **Global Discriminator:** Ensures overall anatomical consistency across the entire liver region.

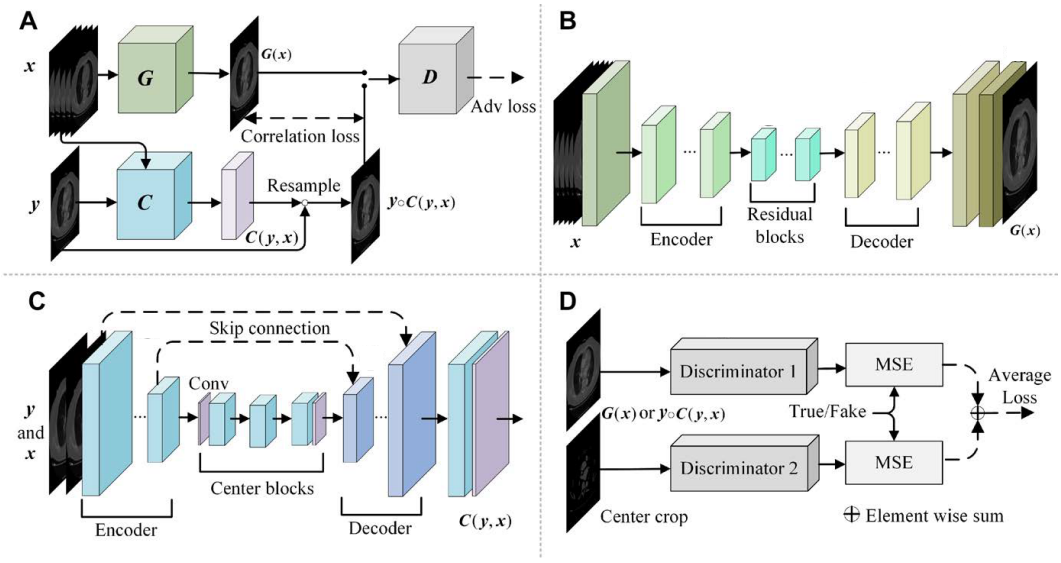

Figure 1: Network architecture of our proposed GAN–based model. Diagrams show the (A) overall architecture, (B) generator architecture, (C) corrector architecture, and (D) discriminator architecture of the model. Note that x denotes the input of the generator, that is, the normalized NCEMRI scan; y denotes the target output of the generator; G(x) denotes the normalized synthetic CEMRI scan produced by the generator; and C(y, x) denotes the correction matrix.

Training Strategy:

- Initial training of the generator using pixel-wise loss functions to establish baseline mappings between NCEMRI and synthetic CEMRI.
- Adversarial training with correction and smoothing losses to refine image quality and diagnostic accuracy.

Loss Functions:

1. **Adversarial Loss:** Ensures synthetic images are indistinguishable from real hepatobiliary phase images.
2. **Correction Loss:** Targets regions with significant contrast changes, such as bile ducts and lesion boundaries, to ensure clinical relevance.
3. **Smoothing Loss:** Minimizes noise and enhances clarity, critical for diagnostic interpretation.

Baseline choice:

In addition to developing our own customized GAN architecture, we utilized CycleGAN and Pix2Pix as baseline and benchmark models to evaluate and compare performance. These models have been widely recognized for their effectiveness in image-to-image translation tasks and provide a reference for assessing our proposed solution's improvements.

4 Implementation

Development Environment:

Training was conducted on a server equipped with four NVIDIA A100 GPUs. This high-performance setup ensured efficient handling of the computational demands of GAN training, particularly for large-scale image datasets. The dataset was managed using Python libraries, ensuring efficient preprocessing and augmentation.

Workflow:

1. Data preprocessing and augmentation tailored for hepatobiliary phase imaging.
2. Model architecture design with a focus on retaining contrast and anatomical details.
3. Iterative training using balanced loss functions to optimize both local and global features.
4. Validation and testing on separate subsets, including radiologist assessments to ensure clinical applicability.

Algorithm Overview:

- Generator: Maps NCEMRI to synthetic hepatobiliary phase images.
- Discriminator: Classifies real versus synthetic hepatobiliary phase images.
- Training loop optimizes generator and discriminator iteratively using Adam optimizers.

5 Numerical Experiments

Evaluation Metrics:

1. **SSIM:** Ensures structural fidelity between synthetic and real hepatobiliary phase images.
2. **PSNR:** Measures clarity and noise levels, with values above 30 dB confirming high-quality outputs.
3. **NRMSE:** Evaluates pixel-wise differences between synthetic and ground-truth images, focusing on penalizing larger errors.

Experiments:

Comparison with Pix2Pix and CycleGAN demonstrated superior performance of the proposed model. Specifically, our customized GAN architecture achieved higher SSIM and PSNR scores while retaining critical diagnostic details. Pix2Pix, while effective in basic structural translation, struggled with preserving fine anatomical features like bile ducts. CycleGAN provided better overall image consistency but lacked the fine-tuning required for hepatobiliary phase enhancements. Our results showed that the customized GAN addressed these limitations effectively. However, radiologists' assessments on this dataset are still needed for comprehensive results.

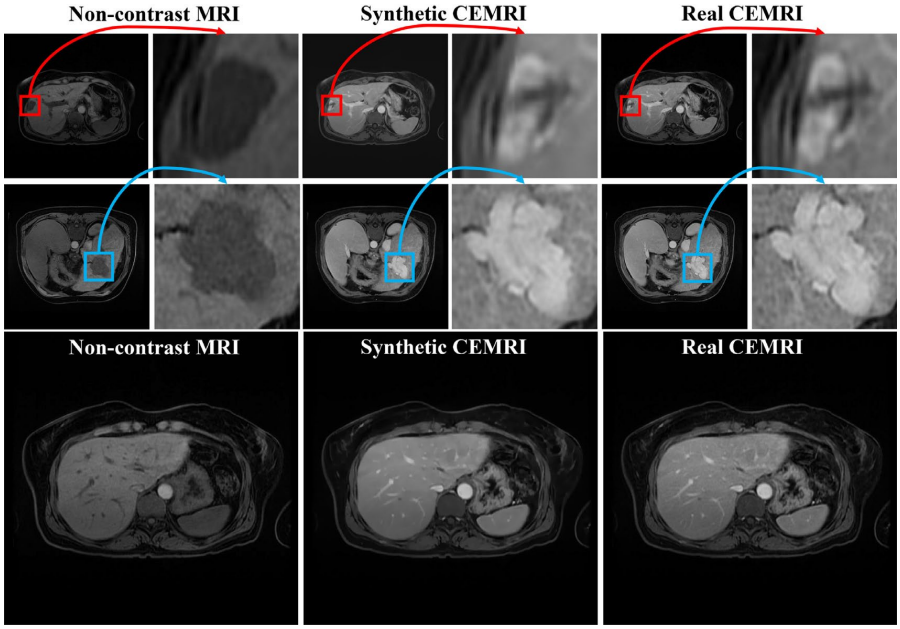

Figure 2: Sample input and output from the model.

	Internal Validation Set			Internal Test Set		
Model	PSNR	SSIM	NRMSE	PSNR	SSIM	NRMSE
CycleGAN	21.05	0.796	0.194	20.86	0.748	0.199
pix2pix	23.32	0.834	0.168	22.87	0.824	0.169
Custom GAN	31.06	0.914	0.146	30.68	0.893	0.152

Table 1: Numerical Metrics for 3 architectures.

6 Answer Research Questions

Can GANs effectively replace Primovist in hepatobiliary phase imaging?

Synthetic images demonstrated comparable diagnostic quality, providing a viable alternative.

What are the limitations of GANs in this context?

Challenges include addressing variability in patient anatomy and scanner settings. Future work should focus on larger datasets and advanced architectures to improve generalizability.

7 Conclusions

This project demonstrates the feasibility of using GANs for synthesizing hepatobiliary phase liver MRI images without Primovist. The work builds upon foundational research by Goodfellow et al. (2014), where GANs were introduced as a revolutionary tool for data generation [2], and applies this in a novel clinical context. By eliminating the need for contrast agents, this approach offers a safer, cost-effective alternative for liver diagnostics. Future work includes expanding the dataset, refining loss functions as seen in works by Jayachandran et al. (2021), and validating results in clinical trials [5].

References

References

[1] J. e. a. Lyu, "Generative Adversarial Network–based Noncontrast CT Angiography for Aorta and Carotid Arteries.," *Radiology,* 2023.

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Appendix

The GitHub link for this project is shown below.

https://github.com/trz0313/ECE1508_Group27