Indian Institute of Information Technology Vadodara (Gandhinagar Campus)

Design Project Report - 2021

On

Medical Image Translation using CycleGAN with Diagnostic verification

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Abstract— **This study explores the application of CycleGAN in translating CT scan images to corresponding MRI counterparts, emphasizing the use of unpaired datasets during model training. Unlike the traditional approach leveraging paired datasets, our research validates the effectiveness of cross-modal image synthesis in medical imaging. This study extends beyond image translation to integrate brain tumor detection, leveraging generated MRI images. Demonstrating the model's proficiency in unpaired translation, it underscores its utility in diverse medical applications.**

Keywords— **CycleGAN, Medical Image Translation, Brain, Tumor Detection, Generative Adversarial Networks (GANs)**

I. Introduction

Magnetic resonance imaging (MRI) stands as a formidable diagnostic tool, offering unparalleled anatomical insights. However, its widespread utilization is hindered by factors such as high costs and limited accessibility. In contrast, computed tomography (CT) scans are more readily available and cost-effective. Nevertheless, CT scans exhibit limitations in depicting soft tissues and specific pathological features, lagging the detailed capabilities of MRI.

This research addresses the dichotomy between MRI and CT scans by exploring the potential of CycleGAN, a powerful deep learning architecture. The objective is to leverage CycleGAN's capabilities to translate CT scans into MRI-like images, aiming to bridge the gap between these two modalities and improve diagnostic accessibility. Furthermore, the study extends its focus to incorporate brain tumor detection, enhancing the diagnostic value of the generated MRI-like images. This multifaceted approach not only seeks to make MRI-like imaging more accessible but also contributes to the early detection of brain tumors, thereby advancing the field of medical imaging and diagnostic healthcare.

II. Literature Survey

A. *Image-to-Image Translation with Conditional Adversarial Networks*

The paper Image-to-Image Translation with Conditional Adversarial Networks [1] proposes a framework for tackling this challenge. It introduces pix2pix, a conditional adversarial network (CAN) approach for unpaired image-to-image translation. Unlike its predecessors, pix2pix eliminates the need for paired data, making it potentially transformative for medical image translation.

The pix2pix Architecture:

pix2pix utilizes two GANs: one for each translation direction. These GANs consist of a generator and a discriminator. The generator maps an image from one modality to the other, while the discriminator attempts to distinguish between real and translated images. This adversarial training process encourages the generator to produce increasingly realistic translations.

A key innovation of pix2pix is the L1 and L2 loss functions added to the adversarial loss. These losses penalize deviations between the translated and ground truth images, further enhancing the translation quality. Additionally, pix2pix incorporates skip connections that directly inject features from the input image into the generator's output, preserving crucial details in the translated image.

Applications in Medical Imaging:

- Colorizing grayscale medical images
- Synthesizing missing data in incomplete scans
- Converting low-resolution images to high-resolution

Strengths and Limitations:

1) Potential for artifacts: As pix2pix relies on deep learning, it can be susceptible to producing artifacts in the translated images, especially in areas with complex anatomical structures.

2) Data requirements: The model's performance depends on the quality and quantity of training data. Large datasets specific to each medical imaging task are often needed for optimal results.

3) Computational cost: Training deep learning models like pix2pix can be computationally expensive and require specialized hardware.

B. A Strictly Bounded Deep Network for Unpaired Cyclic Translation of Medical Images

The paper A Strictly Bounded Deep Network for Unpaired Cyclic Translation of Medical Images [2] proposes a method for unpaired medical image translation, where they presented a rigorously constrained generative network designed to achieve a stable cyclic (bidirectional) translation. This network comprises two cyclically connected conditional GANs, with each generator (consisting of 32 layers) conditioned by the concatenation of alternate unpaired patches from input and target images of the same organ. The fundamental concept underlying this approach is to leverage cross-neighborhood contextual feature information, effectively bounding the translation space and enhancing generalization.

Further, the generators are equipped with adaptive dictionaries which are learned from the cross-contextual patches to reduce possible degradation. Discriminators are 15-layer deep networks which employ minimax function to validate the translated imagery. A combined loss function is formulated with adversarial, non-adversarial, forward-backward cyclic, and identity losses that further minimize variance of the proposed learning machine.

The pCCGAN method offers several advantages:

- Eliminates the need for paired data: This significantly reduces the cost and difficulty of data acquisition.
- Produces high-quality translations: The method preserves image details and minimizes artifacts.
- Reduces errors: The translated images closely resemble the original images.
- Outperforms other unpaired methods: The pCCGAN approach demonstrates superior performance compared to existing unpaired translation techniques.

However, some limitations exist:

- High computational cost: Training the pCCGAN model can be computationally demanding.
- Requirement for large training datasets: The method's performance relies on the availability of a large amount of training data.

III. The Present Investigation

We employed the CycleGAN architecture, consisting of two generative models (G1 and G2) and two discriminative models (D1 and D2). G1 focuses on translating CT images to MRI-like representations, while G2 translates the generated MRI-like images back to the original CT domain. Additionally, a binary classification model for tumor detection was integrated into the pipeline.

Generators: Both G1 and G2 utilize U-Net-based networks, leveraging skip connections for capturing intricate spatial relationships within images. This architecture facilitates high-quality translation between CT and MRI domains.

Discriminators: D1 and D2 adopt pix2pix's patchGAN architecture to analyze local image patches for discerning real from translated images. Simultaneously, a binary classification model evaluates the presence of tumors in the translated images.

Binary Classification Model for Tumor Detection:

We implemented a binary classification model for tumor detection using a dataset comprising both positive (tumor-present) and negative (tumor-absent) samples. The model was trained using a combination of CT images and translated MRI-like representations.

Data preprocessing:

The dataset included unpaired CT and MRI images from various anatomical regions. To ensure model generalizability, we applied image normalization and random augmentation techniques during training, including resizing, cropping, and flipping.

Training process:

The integrated model, comprising CycleGAN and the tumor detection binary classification model, was trained for 50 epochs and 20 epochs respectively. Adam optimizer with a learning rate of 2e-4 was utilized for both the generators, discriminators, and the tumor detection model. Checkpointing was implemented to save progress and allow the resumption of training.

Evaluation:

The model's performance was evaluated through visual inspection and quantitative metrics. Visual comparisons between translated MRI-like images and real MRI images assessed visual quality, while the binary classification model's predictions determined tumor presence. Additionally, L1 loss calculations measured the accuracy of CT image reconstruction from translated MRI-like representations.

CT - to - MRI		
Performance metric	Mean square error	Cosine similarity score
Score values	0.13814	0.89710

Fig.1 Metrics for cycleGAN CT-MRI generator

Tumor-detection			
Performance metric	precision	Recall	F1-score
False	0.80	0.84	0.82
True	0.90	0.88	0.89
Accuracy	-	-	0.86

Fig.2 Metrics for Classification model

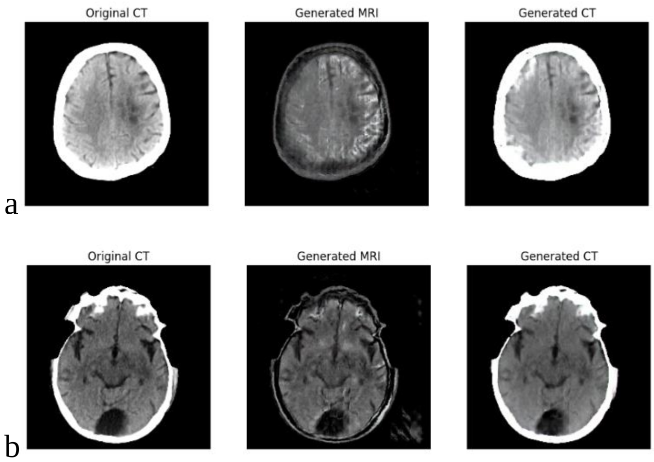

Fig.3 CycleGAN results for (a) Bad-quality CT and (b) Good-quality CT

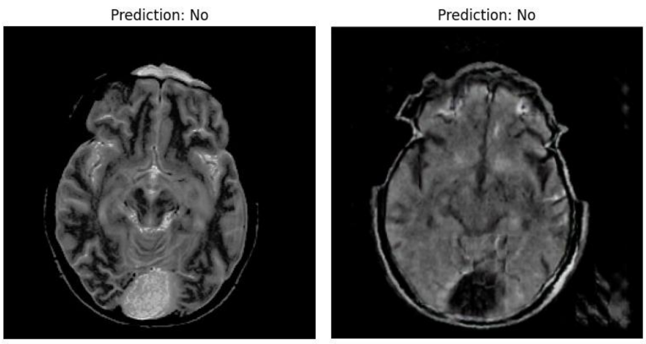

Fig.4 The classification model shows no presence of tumor on ground truth (a) and also on the generated mri (b)

IV. Results And Discussion

Our findings reveal that the cycleGAN method to generate close to real MRIs is plausible. However the generated images need to have little to no noise or structural deconstruction for them to be used for diagnostic purpose.

Our classification model for Tumor Detection reached a decent F1-score of 0.89 for yes and 0.82 for no but in the matter of diagnostic check, the bad quality input image which was retrieved from the cycleGAN results in a false positive prediction of yes even though the actual MRI reports no tumor on it.

The difference in classification predictions show that there is much to be improved on the image generation , however the performance metrics with low MSE of 0.13814 and high cosine similarity score of 0.89710 show that it is still a plausible method to generate the MRIs from a CT using our proposed architecture.

V. Conclusion

This study not only highlights the success of CycleGAN in unpaired CT-to-MRI image translation but also introduces a binary classification model for tumor detection, expanding the model's utility in medical imaging. Our integrated approach demonstrates the capability to generate realistic MRI-like representations from CT images while simultaneously identifying the presence or absence of tumors. This innovative dual-purpose model addresses the limitations associated with paired data requirements in traditional methods, opening new avenues for clinical applications.

Exciting Possibilities for Clinical Applications:

1) Alternative MRI scans: The CycleGAN, coupled with tumor detection, provides alternative options for MRI examinations. This is particularly valuable in cost-sensitive scenarios or for patients with contraindications to traditional MRI scans.

2) Cross-modality comparisons: Translated MRI-like images enable more effective comparison between CT and MRI scans, aiding in diagnosis and treatment planning. The additional tumor detection component enhances the comprehensiveness of the translated images.

3) Enhanced diagnostic capabilities: By highlighting specific anatomical features in the translated images, our model offers the potential to improve diagnostic sensitivity and specificity, contributing to more accurate and informed clinical decisions.

Further Research Directions:

1) Data diversity: To enhance model generalizability, future work should focus on expanding the training dataset to include more diverse anatomical regions and pathologies. This will ensure the model's effectiveness across a broader range of clinical scenarios.

2) Extension to Other Imaging Modalities: Given the successful translation from CT to MRI, there is potential to extend this approach to other imaging modalities such as PET, X-ray, etc. Exploring the translation capabilities across various scans will contribute to the versatility of the model in accommodating a wide spectrum of medical imaging data.

Acknowledgment

We express our sincere gratitude to the Indian Institute of Information Technology Vadodara (IIITV) and Dr. Jignesh Bhatt for their invaluable support and guidance throughout this project. Dr. Bhatt's expertise and mentorship were crucial in shaping the conceptual framework of our study and ensuring the methodological rigor of our investigation. His insightful feedback and continuous encouragement significantly contributed to the successful completion of this project.

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