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Medical image synthesis using GAN

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***Abstract* - Medical images are usually utilized in clinics to produce visual representations of under-skin tissues in human bodies. Medical image synthesis strategies are developed to supply pictures that are very accurate and reasonable. To produce diverse modalities of medical imaging with unique characteristics of visualization, different imaging protocols are used. The scanning of high-quality single modality images or homogeneous multiple modalities of images is very costly These strategies may be accustomed produce pictures of various varieties, counting on the particular desires of a given medical scenario. Among the various deep learning approaches, GANs and CycleGAN became significantly dominant for medical image synthesis in recent years. GAN and CycleGAN has provided new framework for medical image synthesis. this is often as a result of GANs offer a replacement technology and framework for the appliance of medical pictures. GANs do not need loads of labelled data to get correct data, which might be generated through competition between the generator and discriminator networks. Therefore, GANs are quickly proving to be a robust tool for machine learning and AI. X-rays, which create ionising radiation, are used in CT scans. According to research, this form of radiation may harm DNA and cause cancer. In this study, we present a method for converting an organ's MRI scan into a CT scan using cycleGan and a generative adversarial network.**

I.INTRODUCTION

Image synthesis across other imaging modalities, such as PET and cone-beam CT (CBCT), is now feasible and a growing number of applications are benefiting from recent advancements in image synthesis techniques thanks to the quick progress in the fields of machine learning and computer vision over the last 20 years. We can prevent the negative consequences of CT scan by converting an MRI scan into one. X-rays, a form of radiation known as ionising radiation, are used in CT scans. CT scan damages your cell DNA and it also increases the chances that they will turn cancereous. In this project, we offer a method for obtaining a CT scan by translating it from an MRI scan. To create a synthetic and similar medical image from an actual scan related to a certain organ, we will use the deep learning technique of GAN. Synthetic data is information that is artificially manufactured rather than generated by real-world or actual events.

II.PROBLEM DEFINITION

There is a worldwide shortage of radiologists, At the same time, the number of radiology studies is increasing at an unprecedented rate. To keep pace , To keep pace, the average radiologist interpreting computed tomography (CT) and magnetic resonance imaging (MRI) examinations would need to read an image every three-to-four seconds of an eight-hour workday, according to one study.

III.LITERATURE REVIEW

Radiology and radiation oncology both make extensive use of image synthesis across and within medical imaging modalities. Its main goal is to improve clinical workflow by avoiding or substituting imaging procedures when they are impractical due to time, labour, or financial constraints; when exposure to ionising radiation is not permitted; or when image registration introduces unacceptably high levels of uncertainty between images taken using various modalities. These advantages have generated considerable interest in a variety of potential clinical applications, including positron emission tomography (PET)/MRI scanning and MRI-only radiation therapy treatment planning. This field has recently been dominated by deep learning, a large subfield of machine learning and artificial intelligence. To extract relevant features from images, deep learning uses neural networks with multiple layers containing large numbers of neurons. For greater performance on various activities, various networks and architectures have been proposed. The majority of deep learning-based picture synthesis techniques utilise a similar framework for image intensity mapping that is data-driven. The process usually starts with a training stage when the network learns the mapping between the input and the target, followed by a prediction stage where the target is generated from the input. Deep learning-based methods are more generalizable than traditional model-based methods since the same network and architecture for a pair of image modalities can be applied to other pairs of image modalities with little alteration. This enables quick translation to numerous imaging modalities whose synthesis is helpful clinically. We have thoroughly examined new deep learning-based applications and methodologies for generating medical images. We specifically classify current literature according to deep learning techniques and highlight its contributions. Clinical applications are reviewed, together with any relevant restrictions and difficulties. Finally, a summary of current trends and future directions is included.

Review of Existing Models, Approaches, Problems

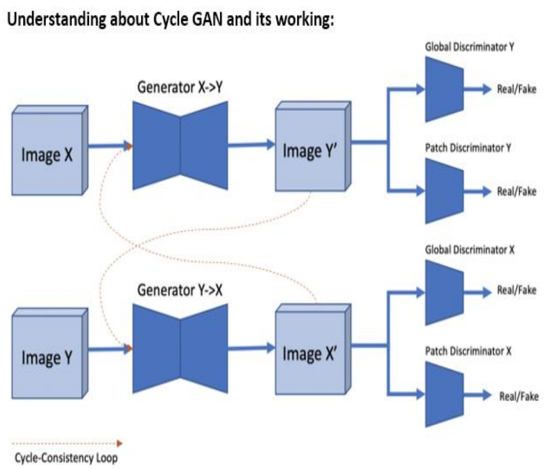
Generative Adversarial Networks (GANs): Impressive results in picture production [6, 39], image editing [66], and representation learning [39, 43, 37] have been attained by [16, 63]. For conditional image creation applications, such as text2image [41], image inpainting [38], and future prediction [36], as well as for other domains including movies [54] and 3D data [57], recent algorithms have used the same concept. The concept of an adversarial loss, which causes the generated images to be, in theory, indistinguishable from real photos, is essential to the success of GANs. Given that this is precisely the goal that much of computer graphics seeks to accomplish, this loss is especially powerful for jobs involving the creation of images. To learn the mapping, we use an adversarial loss so that translated images cannot be discriminated from those in the target domain.

Image-to-Image Translation: The concept of image-to image translation goes back at least to Hertzmann et al.’s Image Analogies [19], who uses a non-parametric texture model [10] on a single input-output training image pair. More recent methods involve CNNs to learn a parametric translation function from a collection of input-output samples (e.g., [33]). Our method expands upon the "pix2pix" architecture developed by Isola et al. [22], which employs a conditional generative adversarial network [16] to learn a mapping from input to output images. Similar concepts have been used for a variety of tasks, including producing photos from sketches [44] or attribute and semantic layouts [25] or other sources. We learn the mapping without using paired training examples, in contrast to the previous research mentioned above.

Unpaired Image-to-Image Translation : The unpaired context, where the objective is to link two data domains, X and Y, is likewise addressed by a number of other techniques. Rosales et al[42] .'s Bayesian framework incorporates a likelihood term derived from numerous style images, as well as a prior based on a patch-based Markov random field generated from a source image. A weight-sharing technique has been used more recently by CoGAN [32] and cross-modal scene networks [1] to develop a common representation across domains. A combination of variational autoencoders [27] and generative adversarial networks [16] is used by Liu et al. [31] to extend the architecture mentioned above concurrently with our approach. While the input and output may differ in "style," another line of concurrent work [46, 49, 2] pushes them to share specific "content" traits. These techniques likewise make use of adversarial networks, but they include further words such class label space [2], image pixel space [46], and image feature space [49] to compel the output to be close to the input in the predefined metric space. Unlike the aforementioned methods, our formulation does not presume that the input and output must reside in the same low-dimensional embedding space, nor does it rely on any task-specific, predetermined similarity function between the two. Our approach is now a general-purpose answer to a variety of vision and graphics problems.

IV.FORMULATION

Our goal is to learn mapping functions between two domains X and Y given training samples $\{x_i\}$ N i=1 where $x_i \in X$ and $\{y_j\}$M j=1 where $y_j \in Y$ 1 . We denote the data distribution as $x \sim p_{data}(x)$ and $y \sim p_{data}(y)$. As illustrated in Figure 3 (a), our model includes two mappings $G : X \rightarrow Y$ and $F : Y \rightarrow X$. In addition, we introduce two adversarial discriminators DX and DY , where DX aims to distinguish between images {x} and translated images {F(y)}; in the same way, DY aims to discriminate between {y} and {G(x)}. Our objective contains two types of terms: adversarial losses [16] for matching the distribution of generated images to the data distribution in the target domain; and cycle consistency losses to prevent the learned mappings G and F from contradicting each other.



Adversarial Loss:
We apply adversarial losses [16] to both mapping functions. For the mapping function $G : X \rightarrow Y$ and its discriminator DY , we express the objective as: LGAN(G, DY , X, Y) = Ey∼pdata(y) [log DY (y)] + Ex∼pdata(x) [log(1 − DY (G(x))], (1) where G tries to generate images G(x) that look similar to images from domain Y , while DY aims to distinguish between translated samples G(x) and real samples y. G aims to minimize this objective against an adversary D that tries to maximize it, i.e., minG maxDY LGAN(G, DY , X, Y). We introduce a similar adversarial loss for the mapping function $F : Y \rightarrow X$ and its discriminator DX as well: i.e., minF maxDX LGAN(F, DX, Y, X).

Cycle Consistency Loss:
Adversarial training can theoretically learn mapping G And F produce the same distributed output as the target. Domains Y and X (strictly speaking, G and F must be probability functions) [15]. but, With enough capacity, the network can map the same thing Set of input images to a random sequence of images Target domain to which each learned mapping can be moved Induces an output distribution that matches the target distribution. Therefore, the loss of the enemy alone cannot be guaranteed. The learned function can map individual input xi To Desirable output yi .. To further reduce the space of possible mapping functions, the learned mappings functions should be cycle-consistent: as shown in Figure 3 (b), for each image x from domain X, the image translation cycle should be able to bring x back to the original image, i.e., $x \rightarrow G(x) \rightarrow F(G(x)) \approx x$. We call this forward cycle consistency. Similarly, as illustrated in Figure 3 (c), for each image y from domain Y , G and F should also satisfy backward cycle consistency: $y \rightarrow F(y) \rightarrow G(F(y)) \approx y$. We incentivize this behavior using a cycle consistency loss: Lcyc(G, F) = Ex∼pdata(x) [kF(G(x)) − xk1] + Ey∼pdata(y) [kG(F(y)) − yk1]. (2) In preliminary experiments, we also tried replacing the L1 norm in this loss with an adversarial loss between F(G(x)) and x, and between G(F(y)) and y, but did not observe improved performance.

Full Objective:
Our full objective is:
L(G, F, DX, DY) =LGAN(G, DY , X, Y) + LGAN(F, DX, Y, X) + λLcyc(G, F), where λ controls the relative importance of the two objectives. We aim to solve: G ∗ , F∗ = arg min G,F max Dx,DY L(G, F, DX, DY).
Note that this model can be considered as training for two "autoencoders" [20]. Learn autoencoder
F ◦ G: X → G ◦ F: Y → Y different from X. However, each of these autoencoders has a special internal structure. Image to oneself through intermediate representation. The image is translated into another domain. like that The setup can also be seen as a special case of a "hostile autoencoder" [34] training with hostile losses. An autoencoder bottleneck layer that matches any target distribution. In our case
X → X autoencoder is for domain Y.

V.PROPOSED SOLUTION

Our main aim is to convert the MRI scan of an organ into a CT scan of same organ. For this purpose, we opted the Deep Learning technique of Generative Adversarial Network. It is a class of machine learning framework that utilises the power of Neural Network. GAN utilizes two neural networks with competitive learning approach: (1) a Generator to produce a new data from the input noise and (2) a Discriminator to discriminate this new data from the training data. These 2 neural networks compete with each other to become more and more accurate. The purpose of a GAN is to generate the data from scratch. For our solution we will use its image-to-image translation application.

GAN Illustration of Architecture: In order to transform MRI data to CT scans, we use a Deep Learning architecture called CycleGAN. Unpaired image-to-image translation is automatically trained using the CycleGAN approach. A unique variation on conventional GANs is cyclic GANs. They can also generate fresh samples of data, but they do so by altering samples of the input rather than starting from scratch. CycleGAN uses a cycle consistency loss to enable training without the need for paired data, and the models are developed using a set of images from the source and target domains that are not associated in any way. With no one-to-one mapping between the source and target domains, it can translate from one domain to another. This straightforward method is effective and produces visually impressive outcomes across a variety of application domains.

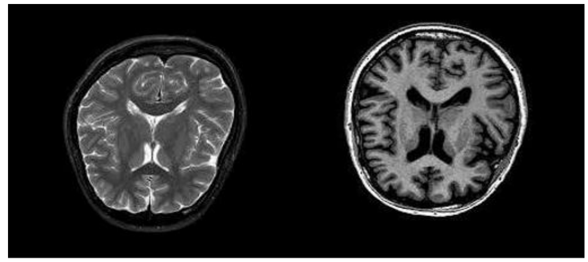
This method can be used, for instance, to change a lion's image into a tiger's image and vice versa.

Cycle GAN: A CycleGan is a neural network that learns how to transform two spaces' worth of information. One of them is change G(x). It changes over a given example $x \in X$ into element of domain Y. The subsequent one is F(y), which changes sample components $y \in Y$ into element of domain X. Two conventional GANs are used in order to learn F and G. A Generator network that learns how to change the data as needed is built into every GAN. The GAN's second generator and first generator, respectively, both learn how to compute F and G. Additionally, each generator is linked to a discriminator that develops the ability to discern between actual data y and synthetic data G. (x).

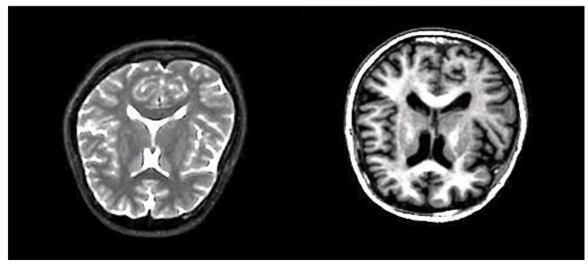
VI.RESULTS

Below are the results obtained after testing on the test images of our dataset.

Real scan images:



Fake/Synthetic scan images:



VII.CONCLUSION

In conclusion we found a solution to our problem statement by using Cycle GAN to convert MRI and CT scans into one another. This in turn provides patients, doctors, and researchers to translate CT scans into MRI scans and vice versa. Thus, we have achieved unpaired image-to-image translation through the technique of Cycle GAN using Grayscale scan images.

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