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Abstract–Radiology is the branch of science that deals with the study of energetic radiations and their use in generating medical images. MRI(Magnetic Resonance imaging) and CT (Computed tomography) are the two widely used modalities in radiology. CT comes with the disadvantage of high radiation risk which may have side effects. Thus, medical image from MRI only radiation which is much safer than CT can be used to synthesize CT images using Deep Learning techniques. In this paper we, propose to build an architecture of Fully Convolutional neural network (FCN) along with a cyclic Generative Adversarial network(GAN). Our model has successfully generated CT images from the given MRI images from an unpaired ADNI image dataset.

Keywords: Deep Learning, Radiology, cGAN, FCN, CT generation, ADNI dataset, MRI

I. INTRODUCTION

Radiology is the branch of science that deals with the study of energetic radiations and their use in generating medical images. Radiology plays a huge role in disease management by providing detailed structural information about disease-related changes. Among the various modalities in this field, CT(Computed tomography) and MRI(Magnetic resonance imaging) are the most widely used ones. In this paper we dive deeper into the opportunities that deep learning structures have in applications in the field of radiology. Computed tomography (CT) comes with the disadvantage of high radiation risk which may have side effects. The lifetime risk posed by a single abdominal **CT** of 8mSv is calculated to be 0.05%, or a one in 2,000 chance of developing cancer. Alternative methods to generate CT should be devised i.e., synthesis of images of different modalities from a single modality. Those can be used for applications where CT images are required but are unavailable, such as in positron emission tomography (PET) attenuation correction in MRI-guided radiotherapy. This is important as it:

- Reduces the risk of radiation from CT
- Reduces the overall time and cost of diagnosis
- Doesn’t depend on the patient to return for getting images of all modalities

We have studied the inherent meaning of radiology and the basic deep learning algorithms that are widely used in the present world. Deep learning has contributed to a series of advances in tackling image recognition and visual understanding problems. Deep learning-based methods have gained pace recently in variety of medical field applications. Thus, our paper aims at

- Applying deep learning methods to generate synthetic CT images from MRI images.
- Comparing other state of art methods to get better results.

In deep learning, Neural networks have been increasing the capabilities of models exponentially. It has proved at par with trained physicians in visually assessing medical images for the detection, characterization and monitoring of diseases. ML (Machine Learning) algorithms have also demonstrated remarkable progress in image-recognition tasks.

Our work aims at using the FCN (Fully Convolutional Network)[1] and cycle consistent GAN (Generative Adversarial Network)[2] algorithms for synthesis of CT image from MRI. With the usage of a GAN framework, we can excel at improving assessments of radiographic characteristics. Medical imaging of different modalities together cost higher and radiation dose is more. MRI only radiotherapy can drastically decrease time, cost and risk of diagnosis. Generative Adversarial Networks can be applied to increase accuracy of the model.

II. LITERATURE REVIEW

Segmentation is a popular approach which partitions medical images into different meaningful segments. Medical images can be represented using one or more Atlases. An Atlas is a model generated by learning parameters on training a data set containing a number of specific images. Atlas based segmentation [3] is the process of segmenting unseen images based on manually labelled images which forms the Atlas. This paper [4] aims at comparing 6 MRI based synthetic CT image generation methods. This paper [4] also indulged in organ auto contouring based on the methods evaluated. Among the 6 methods 4 were Atlas based methods - median of atlas images (A-Median) , atlas-based voxelwise weighting (A-VW) , bone enhanced atlas-based voxelwise weighting (A-Bone), iterative atlas-based voxel-wise weighting (A-Iter) . A voxel represents the average of itself and its neighbours when the brain images are considered. Voxel wise comparison gives us the local concentration difference amount in the brain tissues. The 5th method used deep learning convolutional neural networks and the 6th one was based on tissue segmentation based on two classes- water and air. This paper considered medical images of patients containing image-image linked MRI and CT images of the areas such as bladder, rectum and bone. This paper [4] found out that DL CNN resulted in a better performance giving dice matrices of 0.93, 0.90, 0.93 respectively.

This paper [5] used four different MRI protocols to generate synthetic CT images. The 4 protocols included T1- or T2-weighted MRI, Dixon MRI, UTE MRI (RESOLUTE), and ZTE MRI. The study [5] found that Dixon MRI was more efficient in producing accurate CT images while ZTE MRI provided deeper understanding of the bowel air distribution. They used a data set of 26 patients with 10 of them for training and 16 of them for validation. MRI images for pelvic region was considered. They used a N4 bias correction method for pre-processing and a deep-convolutional neural network(DCNN) for synthetic image generation. The study suggested further work on optimization of MRI inputs features such as spatial resolution and degree of contrast. They also suggested evaluation on ZTE MRI of brain region that includes distinguishing bone and air in the sinuses for evaluation.

This paper [6] explained the advantages of CT scans over rRt-PCR. rRT-PCR is a variation of PCR(Polymerase Chain Reaction) used in COVID-19 testing purposes. rRt-PCR Is a resource intensive method and relatively less sensitive for COVID-19 testing. They used a data set containing 829 lung CT slices from 9 patients. This paper pointed out how synthetic CT images can save the medical staff from the high risk of communicating COVID-19 from the infected patients. They applied a deep learning algorithm based on conditional generative adversarial network that successfully generated realistic COVID-19 CT images based on a segmentation map provided. The work [6] was further improved with the proposed multi resolution discriminator by following the patch GAN method.

The goal of this paper [7] was to synthesize arterial spin labelling (ASL) image which is an important fMRI module. ASL images are useful in diagnosis of diseases such as dementia. The paper designed a deep discriminant learning based model along with a ResNet substructure. The model consisted of 3 branches having a number of ResNet substructures. This research also considered remodelling of the substructure by using 3 blocks: Input block, Basic block and Bottleneck block. They [7] successfully synthesized ASL images which passed the voxel based PVE (partial volume effects) correction tests. They suggested future work on synthesising ASL from images in ADNI data set.

This study [8] aimed at reducing the blurriness in target images that are generated. They proposed a fully convolutional network (FCN) to synthesize

CT images from source MRI images and then use adversarial learning strategies along with an auto context model (ACM) to increase the quality of the artificially generated images. The usage of the difference in image gradient as the loss function helped in reducing the blurriness of the target images. They successfully generated CT images from MRI and 7T MRI images from 3T MRI images. The study [9] also successfully used a similar approach of FCN combining a U-net to generate sCT images from given MRI dataset.

The aim of this paper[10] was to synthesise CT images from MR images by using a residual learning based U-shaped deep neural network (RUN). In residual learning the skip connections in a residual block between layers add output from previous layers to output of stack layers thus training deeper networks. This paper handles the degradation problem in neural networks when it gives higher training error as the deepness of the model increases suitably. The run network in this paper had 16 residual units. It applied the algorithm on a data set of 35 patients that had more than 5000 T1/T2 weighted MRI and CT image pairs they achieve the mean absolute error of 66.12 ± 5.95 HU. This paper [10] pointed out the limitation of having data set related to only the head region of the body.

In this research [11] the author evaluated a data set of the lumbar spine from the SpineWeb library data set having a total of 18 patients with both MRI and CT images. A fully unsupervised model was trained. Normalization and segmentation of vertical bodies and pedicles were done by first designing a fully convolutional network and then cascading a FC-ResNet to it. They successfully applied a pseudo 3D cycle GAN architecture along with a cyclic loss function for the generation of CT images from MRI images. They [11] achieved an average mean absolute error of 125.65.

The aim of this paper [12] was to apply state-of-art Atlas based methods to produce pseudo-CT. This study pointed out the limitation of lack of work on regions other than the head and neck region data sets. They also noted there are a smaller number of datasets where CT and MRI images are paired. Thus, they used a discrete optimization registration framelet with a self-similarity based metric to generate the CT atlas from the respective patient anatomy. The model was tested on dataset of 3D-CT and 3D-MRI whole body scans of the Visceral Concept Extraction Challenge in Radiotherapy. The study compared and made improvement on all previously tested Atlas based models but did not compare atlas-based methods to machine learning approaches.

In this research [13] the author made an alternative improvement to the existing generative adversarial network model, GANai, where new images are composed from source images keeping a high level goal that leads to the synthesis of images having similar standard to the original ones. This resulted in technical improvements such as phase specific loss function, phase specific training data and usage of ensemble learning. This study also pointed out the disadvantage of analysing large scale CT images due to non-standardised imaging protocols which disrupt the radiomic features. They used a data set containing 2448 chest CT images of lung cancer patients that was collected at University of Kentucky medical center. The stability of the proposed model was evaluated using the metrices of cumulative sum control chart (CUSUM) where a value of 0.13 was found for GANai model.

In this research [14] the author successfully used the DECNN model to synthesise CT images from given T1 weighted MRI image dataset giving a MAE(mean absolute error) of 42.5 and PSNR(Peak signal-to-noise ratio) of 33.5.

On reviewing the literature, we have observed the following defects

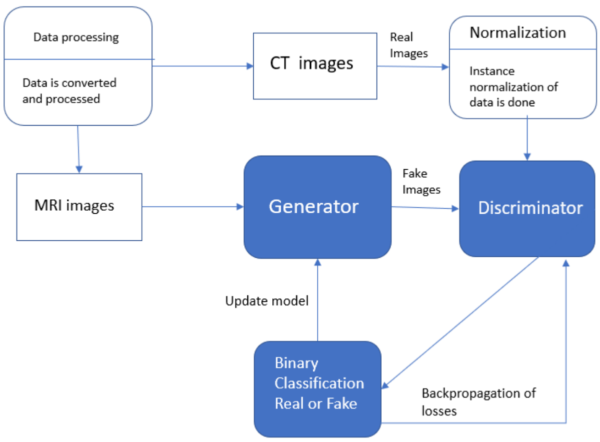
- There are lesser number of paired MRI and CT images datasets.
- Deep neural networks seemed to get more training errors as they got deeper
- Number of whole body scan datasets are lesser
- Data is available in raw format and thus, paired datasets are less in number

Many theories have been proposed to explain the various methods that can benefit the task of image recognition and generation in an efficient way. Although the literature covers a wide variety of methods, our work will focus on two major algorithms which emerge repeatedly throughout the literature reviewed. These elements are:

- FCN
- Cycle consistent GAN.

III. PROPOSED MODEL

GAN starts with producing random noise and goes on to produce high quality CT images. Deep neural networks have been previously used for supervised learning however GAN uses neural networks for the purpose of generative modelling. In this, images which closely resemble images from the original data set are generated by discovering the regularities in the source data images. We can observe the working of a GAN in the following figure(1).



Figure(1). Data Flow diagram for GAN

We will be designing a FCN model to execute the job of generating the target image given a source image. To incorporate a non-linear mapping on the given data of unpaired images of CT and MRI scans we have used the cycle consistent GAN architecture. Cyclic GAN is an unsupervised architecture that does image-to-image translation on unpaired datasets, i.e., where target and source images are not linked to each other

3.1. DATASET

We have used the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. It consisted of unpaired datasets of CT and MRI scans of 15 patients. A total of 315 images were used. The data was in DICOM file format which was processed using pydicom package.

3.2. METHOD

A Generative adversarial network has two different neural networks a generator network and a discriminator network. The input to a generator model is a random vector containing noise that generates an image. The discriminator network distinguishes between the real images and the generated images from the generator.

1. *Pre-processor*: Image_folder class from torch vision has been used to load the data. The image has been resized to a dimension of 64 X 64 px and batch size is set to 128. The pixel values are then normalised with the following values each channel and a range of (-1,1) is set .

- Mean=0.5
- Standard deviation=0.5

2. *Helper functions*: These were used to de-normalize image. Torch vision utility function make_grid was used to display images in the batch. A function denorm was used to de-normalize the values back to a range of (0,1). In the same module we display the grid of images to visualize the working of the model.

3. *Parameters*: The parameters used for training the model is noted in the table(1) below.

Table (1). Training Parameters

Parameters	**Description**
lambda_ABA *lambda_BAB*	Sets the cycle consistency loses
learning_rate_D *learning_rate_G*	Learning rates for generator and discriminator
generator_iterations *discriminator_iterations*	Times every batch of image is trained
synthetic_pool_size	Sets size of the image pool
beta_1 and beta_2	Parameters for Adam optimizer
batch_size	Number of images for each update
epochs	Number of training epochs

4. *Discriminator network*: The discriminator's work is to take a batch of images as the input parameter and the try to distinguish the discriminated image and the real image. We are using a fully-convolutional neural network (FCNN) to output a number for each image. This number indicates the probability that the image was derived from the real data set. Conv2d layers were used with a kernel size of 4 and stride if 2. After which a Batch

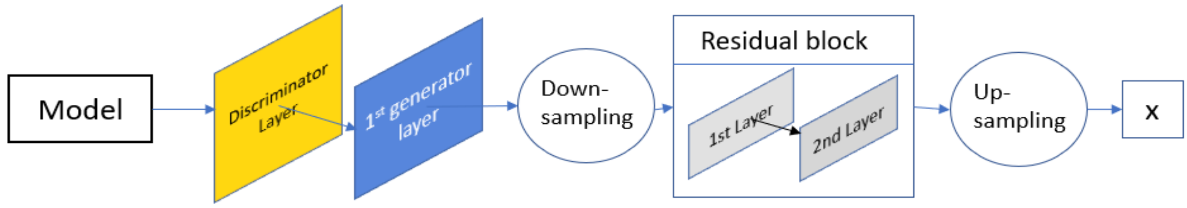


Figure (2) describes the various layers of implementation in the model.

normalization was done by BatchNorm2d function. Following this a LeakyReLU activation function was applied. The final output is flattened from a 1x1x1 tensor to a single vector and finally sigmoid function is applied.

5. *Activation function*: ReLU is a function that simply ignores negative values. Leaky ReLU is a variation of ReLU where it allows a slight amount of negatively valued gradient descent signal to pass (equation (1)). It is varied by the alpha variable a. It overcomes the limitation of ReLU where a lot of output from the generator is lost.

Parametric ReLU: y= ax (1)

In equation (1) value of 0.2 is used for a.

6.*Generator network*: The input to a generator network is a matrix of random numbers. Generator network performed the conversion of the latent tensor into an image tensor having shapes (128,1,1) and (3,28,28) respectively. ConvTranspose2d layer available in PyTorch is used. Latent size of 128 is used. Kernel size of 4 and stride of 1 was used. After that Batch normalization was done and ReLU activation function was used. In addiction a Tanh function was used. This function reduces values in range of (-1, 1).

7. *Layers*: The individual layers used to train the model is shown in the above figure(2)

8. *Discriminator training*: Discriminator indicates whether images real or not. Thus, it is a binary classification model having classes real image or fake so we use the binary-cross-entropy[15] loss function (equation(2)). Discriminator function takes real images and opt_d argument as input. Opt_d optimises the parameters from the discriminator. We generate fake images using the generator and pass those through discriminator and get the fake loss. On passing real images to the discriminator, we get the real loss. The overall loss for the discriminator is the summation of both losses. Finally, we perform optimization of the discriminator by adjusting the weight to so that, the next batch of generated images are slightly better.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

(2)

In equation (2) entropy H is calculated. y is the label and p(y) is the probability of the point belonging to one class for all N points.

9. *Generator training*: Loss function consists of the output from discriminator used to train the generator. Firstly, we generate fake images and then the target labels are set to real valued output of 1 which means real image class output satisfying our primary aim. Gradient descent is performed based on the loss that was out after the binary classification and it was backpropagated to the generator. This resulted in change of input weights to the generator so that it gets better at" fooling" the discriminator. Thus, it starts giving us real life images.

10. *Loss functions*: MAE (Mean Absolute Error) and MSE (Mean Squared Error) are considered to calculate cycle consistency losses.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (3)$$

In equation (3) MAE is calculated by taking the average of the distance between predicted values(y) and real values(x) over n data points

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2. \quad (4)$$

In equation (4) MSE is calculated by taking the average of the square of difference between the observed value(Y) and the predicted value(Y')

IV. EXPERIMENTAL RESULTS

On implementation of the designed adversarial deep learning techniques, Fully-Convolutional Neural Network (FCNN) along with a cycle consistent Generative Adversarial Neural Network we have successfully achieved our aim of generating Computed Tomography images synthetically from the given MRI images. A comparison between the real and fake synthetically generated images are shown in the figure(3) bellow.

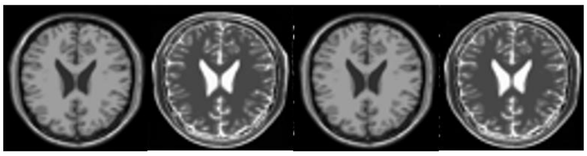


Figure (3) the 1st and 2nd images represent real MRI and CT scans respectively and the 3rd and 4th images represent the synthetically generated images.

Initially the generator loss can be seen as 15.43, on proceeding the value decreases and finally we get a value close to 2.029 after training for up to 200 epochs. We have visualised the effect of changing loss over time. We can observe that the generator loss has come quite close to the discriminator loss. The output loss values have been tabulated in the Table (2) below.

Table (2). Output Losses

Output Losses	Values
ABA_reconstruction_losses	0.001313
BAB_reconstruction_losses	002047
DA_losses	7.12E-06
DB_losses	3.99E-05
D_losses	4.70E-05
G_AB_adversarial_losses	0.998336
G_AB_adversarial_losses	0.997466
G_losses	2.029403
reconstruction_losses	0.00336

We have visualized in figure(4) the working of our model with a line graph below. The x label indicates the ephocs and the y label indicates the losses. On observing the graph we can see that the generator loss line(G_losses) has come close to the discriminator loss line(D_losses). This indicates the success of the designed model.

Figure (4). Graph to indicate loss over time

V. CONCLUSION

Radiation risk in certain Radiological modalities can result into adverse effects on the patient undergoing diagnosis. It is important to device methods to artificially generate medical images of other modalities without actually scanning based on scans of lower radiation risk. We intend to help the doctors in diagonising under lower cost and lesser time. Experimental results show that Deep Learning architectures FCNN combined with cycle consisten GAN has been successful in generating Synthetic CT images from a source dataset of MRI images. This helps the medical professionals in MRI-only Radiotherapy. Thus, this reduces various constraints of time, cost and the availability of the patients for getting the CT scans. It results in faster diagnosis with the patient being exposed to much lesser risk of radiation.

VI. DISCUSSION

Limitations of the model:

- Larger datasets take a longer time span to train and the complexity increases.
- The ADNI dataset consisted of head Scans only.

Future work:

- The synthetically generated CT images can be utitlized to predict Alzheimer's disease and compared with results from prediction using real images.
- Modification on GAN network can be made such as using a Wasserstein GAN can be experimented.
- Whole body scans can be tested on with the proposed model.
- The N4 bias structure can be used at the input to further normalize it.

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