Conditional Generative Adversarial Network Based Metal Artifact Reduction in X-Ray Computed Tomography Images

CS4090 Project

Final Report

Submitted by

Akarsh Joice	**(B160148CS)**
Binil Babu G	**(B160253CS)**
Thomas Philip	**(B160046CS)**

Under the Guidance of

Dr. Jayaraj P. B.

(Assistant Professor)

Dr. Pournami P. N.

(Assistant Professor)

Department of Computer Science and Engineering

National Institute of Technology Calicut

Calicut, Kerala, India - 673 601

June, 2020

NATIONAL INSTITUTE OF TECHNOLOGY CALICUT
KERALA, INDIA - 673 601

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

Certified that this is a bonafide report of the project work titled

CONDITIONAL GENERATIVE ADVERSARIAL NETWORK BASED METAL ARTIFACT REDUCTION IN X-RAY COMPUTED TOMOGRAPHY IMAGES

done by

Akarsh Joice
Binil Babu G
Thomas Philip

of Eighth Semester B. Tech, during the Winter Semester 2019-'20, in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering of the National Institute of Technology Calicut.

	(Dr. Jayaraj P.B.)	
	(Dr. Pournami P.N.)	Dr. Saleena N
Date	**Project Guides**	**Head of the Department**

DECLARATION

We hereby declare that the project titled, **Conditional Generative Adversarial Network Based Metal Artifact Reduction in X-Ray Computed Tomography Images**, is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or any other institute of higher learning, except where due acknowledgement and reference has been made in the text.

Place : NIT Calicut

Date : 13.6.2020

Name : Akarsh Joice
Roll No : B160148CS

Name : Binil Babu G
Roll No : B160253CS

Name : Thomas Philip
Roll No : B160046CS

Abstract

The reduction of metal artifacts in CT imaging poses a serious challenge in the field of medical imaging. Computed Tomography is a diagnostic imaging modality used to create detailed images of internal organs, bones, etc. in order to detect tumors or other abnormalities. Metal artifacts are produced in X-ray CT images due to the presence of metal implants which results in loss of vital information. There is a large scope for the application of computational techniques in the domain of metal artifact reduction. In the past, basic methods like linear interpolation and sinogram in-painting have been used as a makeshift solution to overcome this problem but have produced unsatisfactory results. Recent years have indicated that deep learning techniques have shown great potentials for computer-aided diagnosis and medical image analysis of some diseases such as diabetic macular edema classification, MRI brain tumor segmentation, and mammogram classification. In this project, advanced deep learning approaches for the reduction of metal artifact effect are explored. Two supervised models are built which work in the projection domain, namely, a Conditional Generative Adversarial Network(CGAN) model and a standard CNN-based model to perform a comparative analysis with the former. The training of these models is aided with the learning of simulated artifacts as well. Through the experiments, it is observed that the CGAN model yields better results when compared to the CNN model as seen with their scores on the metrics of evaluation as well as the images generated. This project was done in collaboration with the MVR cancer centre in Kozhikode.

ACKNOWLEDGEMENT

We would like to express our deepest appreciation to all those who helped and supported us in completing this project. We are highly indebted to our project guides, Dr. Jayaraj P. B. and Dr. Pournami P. N. for their constant guidance and supervision in guiding us through this project.

We would like to express our gratitude towards Dr. Saleena N, Head of Department of Computer Science and Engineering, and Dr. K. A. Abdul Nazeer, Project Coordinator, for providing us this platform. We would also like to thank MVR Cancer Centre, Kozhikode for providing us the dataset and clarifying various doubts regarding the topic.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Computed Tomography - CT is a diagnostic imaging test used in neurology and neurosurgery to create detailed images of internal organs, bones, soft tissue and blood vessels. CT works on the principle wherein X-rays are applied in a circular motion with detectors placed on the other side of the body. Body tissue slices are reconstructed and displayed on a gray scale matrix. Level of attenuation is proportionate to the density of the tissues so low density regions show up dark and high density regions(bone) show up bright on the CT image. CT imaging is critical in detecting tumors, finding blood clots and other abnormalities in the body. They also find importance in planning for radiotherapy cancer treatments as it's used to figure out the dosage required in every stage according to how the tumor responds to the treatment.

Metal Artifacts - The presence of highly attenuated metal implants in patients like prosthetic hip, dental fillings, coiling, etc. cause severe beam hardening, photon starvation, scatter, and so on. This in turn leads to strong streak or star-shaped artifacts to the reconstructed CT images which results in difficulties when planning for treatment due to misinterpretation of data. Fig. 1.1 shows some examples of CT images affected by metal artifacts.

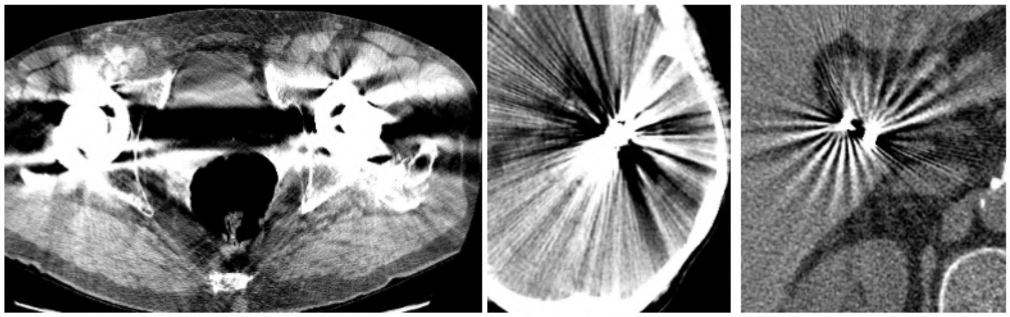

Figure 1.1: CT images exhibiting streak effect due to metal implants

MAR - Metal artifact reduction is the process of removing or reducing the size and intensity of the streak effects in CT images caused due to the presence of metal implants. Although there have been many methods proposed during the past few decades, there still exists no highly accurate way to completely remove metal artifacts and thus poses as an interesting challenge in the X-ray CT imaging field. Traditional methods like sinogram in-painting, linear interpolation and beam hardening correction were used as stopgap measures for artifact reduction and haven't attained satisfactory results and this can be seen in Fig. 1.2 [2]. Since deep learning has attained considerable success in the field of pattern recognition and image processing, it is used as a method for the reduction of metal artifacts. Advanced deep learning approaches which have observed good success are Fully Convoluted Networks(FCN) and various types of Generative Adversarial Networks(GAN).

In this project, a model based on the concept of GAN is developed to achieve metal artifact reduction and its performance is then compared with a standard CNN model. Chapter 2 of this report deals with the background of this domain and works related to it. Chapter 3 defines the problem as well as the input and output of the implementation. Chapter 4 describes the methodology and the overall working of the two models. Chapter 5 lists out the results obtained and discusses the implications of it.

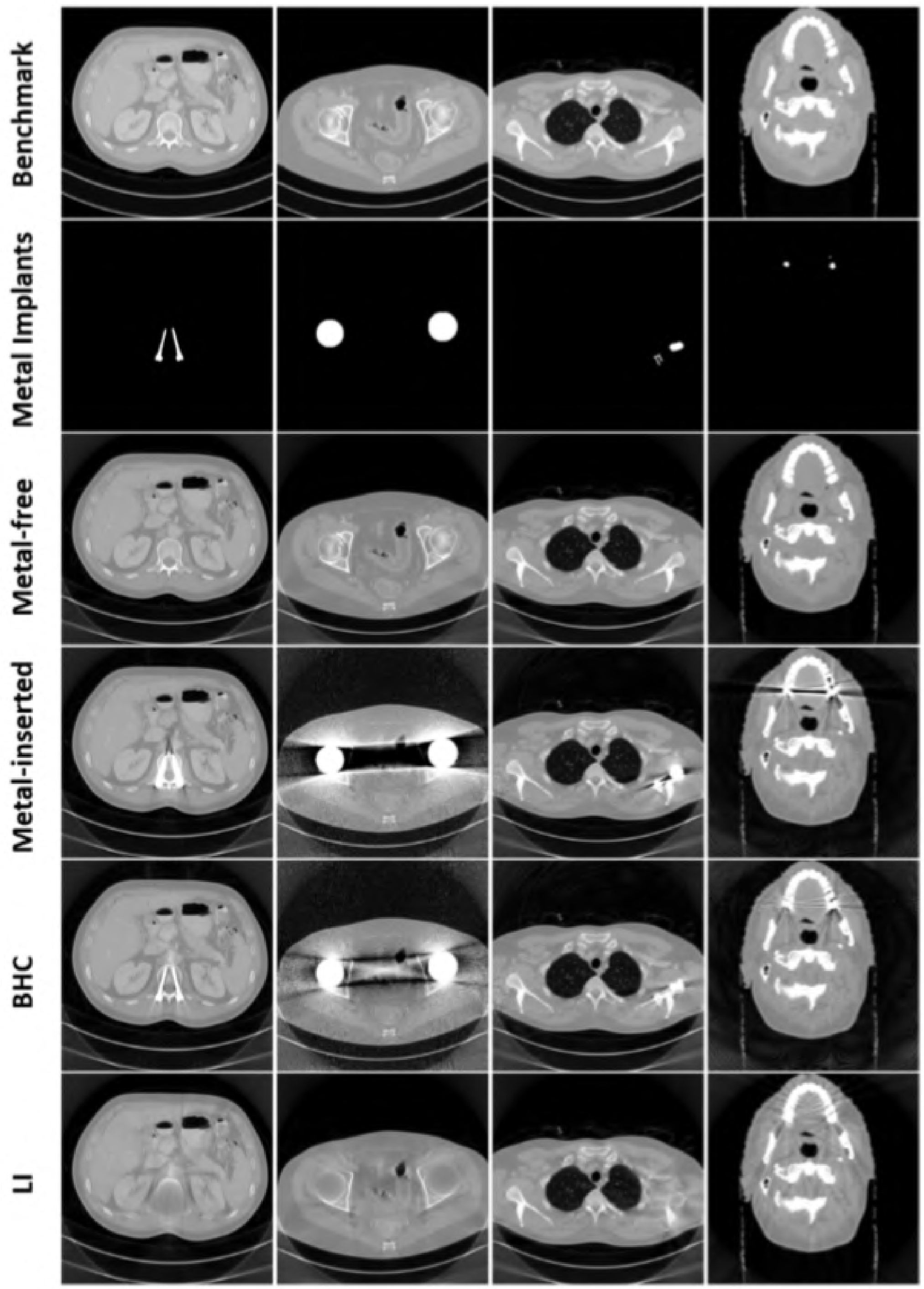

Figure 1.2: Metal artifacts and basic methods like linear interpolation (LI) and beam-hardening correction(BHC) used for its reduction

Chapter 2

Literature Survey

2.1 Background

Many works related to the reduction of metal artifacts in medical imaging involve working in the sinogram domain using standard CNN-based approaches but in these years GANs have attained importance in the field of medical image processing. So it was decided to implement a supervised GAN-based model that works in the projection (sinogram) domain. A Generative Adversarial Network (GAN) is a type of machine learning framework that consists of two neural networks, a generator and discriminator, that essentially participate in a zero-sum game with each other as a means to better train one another. The next section deals with various works that describe their methods to reduce metal artifacts.

2.2 Related Works

Convolutional Neural Network based MAR - In [2], a hybrid of techniques is used to carry out metal artifact reduction with convolutional neural networks being used as the focal point. Metal artifact reduction is carried out generally with the help of three main algorithms which are namely:-

- Correcting physical effects like beam hardening and photon starvation directly which however yields unsatisfactory results in the presence of high-atom number metals.

- Linear Interpolation in projection domain which is done by filling in missing information by making use of surrounding unaffected projections. However this results

- Iterative reconstruction from the unaffected projections or weighted/corrected projections with proper regularizations ensure suppressed artifacts in the reconstructed image.

The CNN-MAR approach proposed by the authors consists of five main steps which starts with metal trace segmentation. This is followed by artifact reduction using beam hardening correction and linear interpolation which is used as training data for the convolutional neural network. Then a CNN prior image is generated from the CNN image obtained earlier using tissue processing. Finally, the metal affected projections are replaced with the forward projections of the CNN prior, which is then followed by Filtered Back Propagation(FBP) reconstruction.
From the research, the authors find that there is a complementary relationship between CNN and the tissue processing by efficiently suppressing artifacts and preventing tissue misclassification.

Deep Learning based Sinogram Correction for MAR - In [3], the authors use deep-learning methods to directly correct the sinogram images obtained from CT before reconstruction. The work is mainly targeted towards applications in airport luggage screening where the presence of metal clutters cause streaking and beam hardening effects in the image. The work is done completely in the sinogram domain and a network is trained over the entire sinogram. The authors make use of a 20-layer fully convoluted network(FCN) to train the data. Their approach involves the following steps:-

- Metal segmentation from the FBP reconstructed image.
- Then the metal-corrupted sinogram is fed to the trained FCN to obtain the corrected sinogram.
- Finally, the FCN corrected sinogram is reconstructed using FBP along with the insertion of the metal image obtained earlier.

This method is claimed to have effectively corrected the sinograms having structure and intensity values similar to the targeted ones.

Fast Enhanced CT MAR using Data Domain Deep Learning - Similar to the previous paper [3], this paper [4] aims to decrease metal artifacts in CT images by applying deep learning in the projection-domain before image reconstruction. In this approach the metal-corrupted data is entirely removed and a conditional generative adversarial network(CGAN) is trained to carry out sinogram data completion. The main contribution of this research is the Deep-MAR framework based on Convolutional Neural Network with its heart being the CGAN framework which consists of a generator network and a discriminant network.
The method begins by passing a metal-contaminated sinogram and reconstructing it using FBP to identify and delete the metal-contaminated data from the sinogram. This is then fed to the generator network which learns to complete the sinogram. The discriminator network learns to classify the real sinogram and the sinogram completed by the generator, and is used as an penalising factor to train the generator network so as to produce realistic output. The workflow diagram of this implementation is depicted below in Fig. 2.1
Reducing Metal Artifacts in CT Images via Deep Learning - The main objective of this paper [5] is to reduce streak artifacts in critical image regions outside the metal object by combining a CNN with a Normalized Metal Artifact Reduction(NMAR) method. NMAR is regarded a state-of-

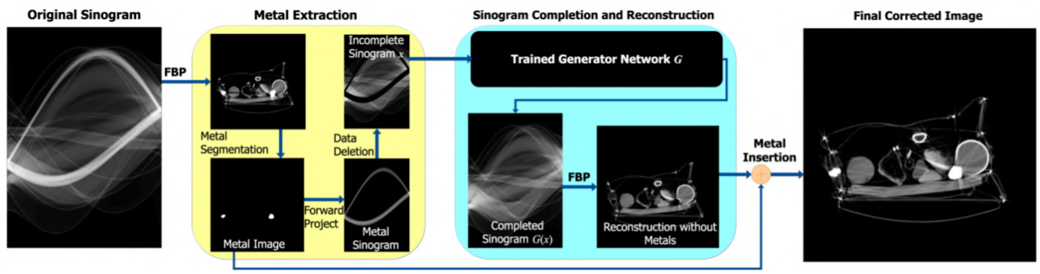

Figure 2.1: Workflow and components of the Deep-MAR framework

the-art method that employs interpolation and normalization to correct data in the metal trace. The network is trained to create an end-to-end mapping of patches from metal-corrupted CT images to their corresponding artifact-free ground truth. The CT images are initially corrected using NMAR which is then fed to a CNN consisting of 6 layers. Each of these layers is followed by a rectified linear unit(ReLU) to create non-linearity. It was found that a significant increase in the quality of the image is achieved upon applying deep learning to the image obtained from NMAR.

2.3 Motivation

Generally most artifact reduction tools used in centres are embedded within proprietary systems whose code cannot be edited or updated according to required needs. The main aim through this project is to serve the community by releasing an open source framework which would enable easy access to an inexpensive but efficient tool to solve the problem of metal artifact in CT images used in the medical field. This would in turn help save the lives of many which would otherwise be at risk due to poor data interpretation.

Chapter 3

Problem Definition

To reduce metal artifacts in CT images by using a Conditional GAN model. The metal-contaminated CT image in DICOM format is given as input. The required output is the reconstructed CT image after the reduction of metal artifact.

Chapter 4

Methodology

Two models were built, namely, a Conditional Generative Adversarial Network (CGAN) model and a standard CNN model to carry out metal artifact reduction in the sinogram domain. This chapter describes the stages involved in the implementation of the two models as well as its overall design. A comparison was made based on the performance of the two models and the results are listed in the next chapter. Fig. 4.1 depicts a brief overview of the entire process involved. The following sections describe the various stages involved in carrying out our implementation of the models.

4.1 Preprocessing

Before feeding the input to the CGAN model, the CT data undergoes multiple rounds of preprocessing. This begins by importing the CT dataset and making each slice into numpy pixel arrays whose values are converted into Hounsfield Units. These images are then transformed into their corresponding sinograms in the projection domain by applying the radon transform(Fig. 4.2). From the original image, we obtain the metal-only image by applying a threshold function which is followed by erosion and dilation(for finer quality). This image is then transformed into the corresponding metal-

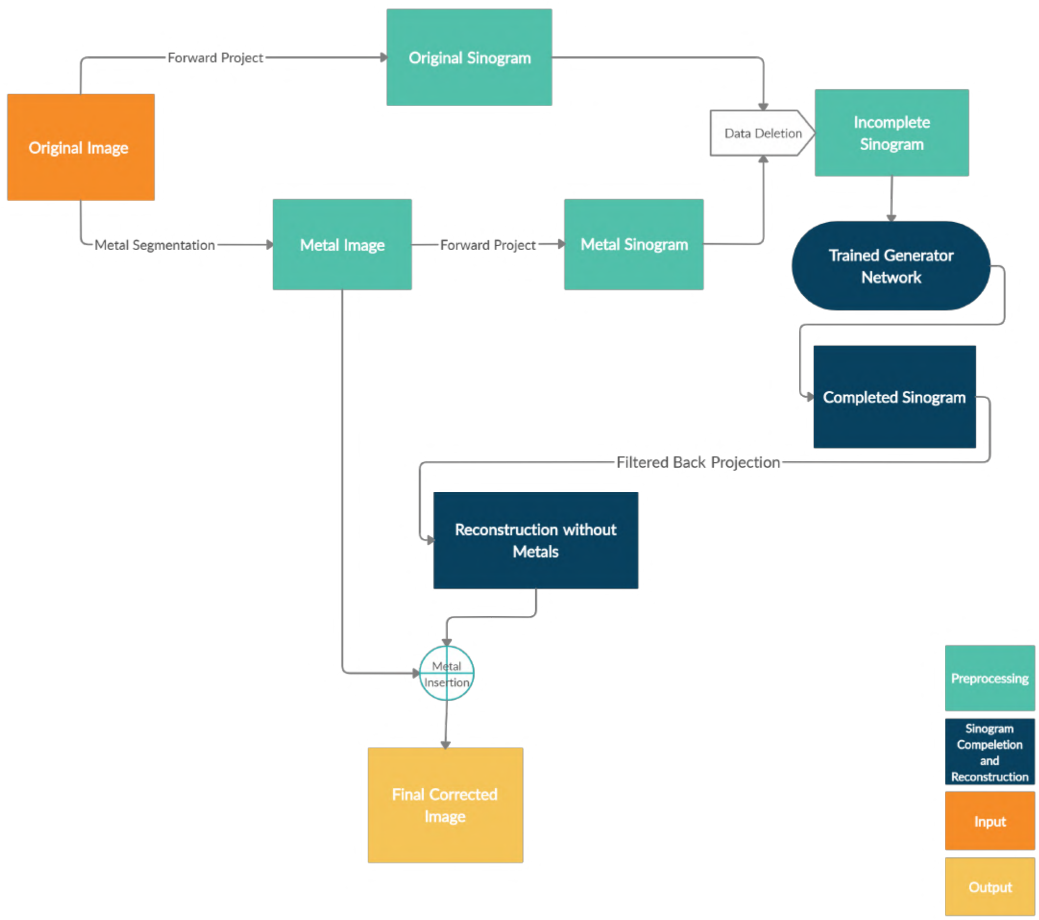

Figure 4.1: Work flow diagram

only sinogram(Fig. 4.3). The sinograms obtained above are subject to normalization to scale the values in the range 0-255. Finally the metal-only sinogram is deleted from the original sinogram which then becomes the input to the two models(Fig. 4.4).

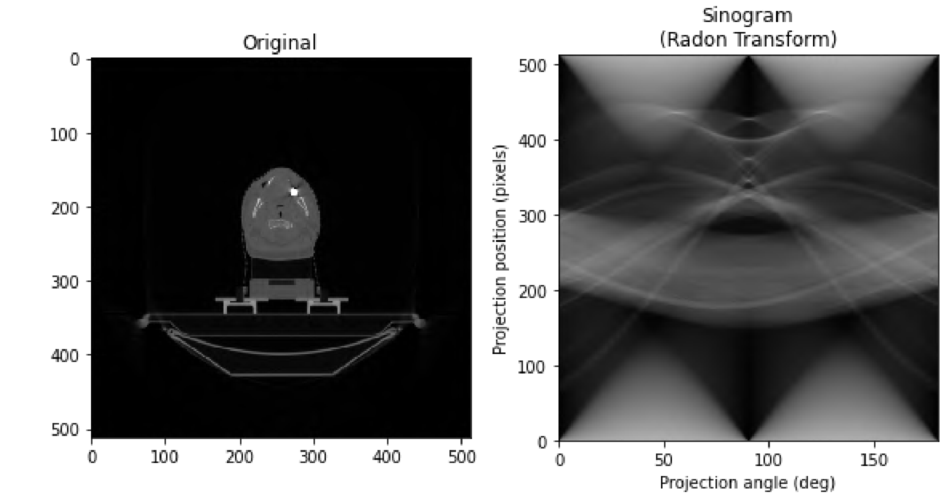

Figure 4.2: Metal-corrupted image and its Sinogram

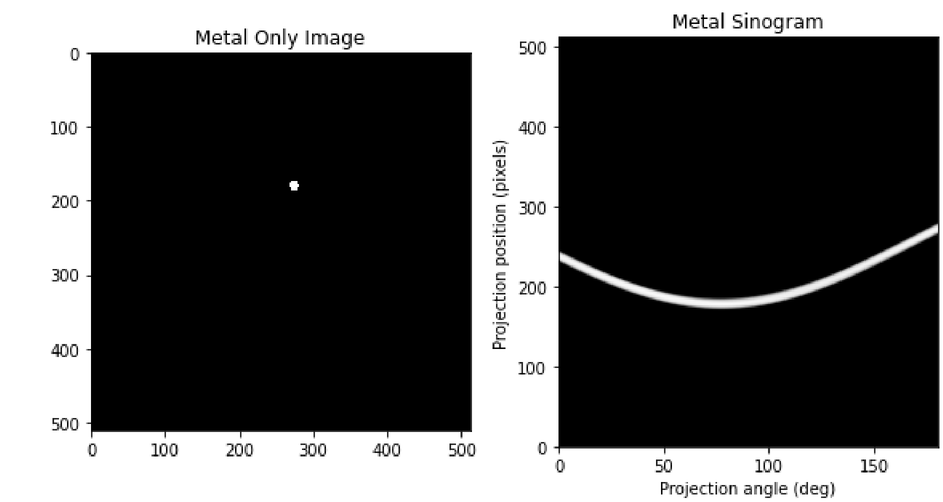

Figure 4.3: Metal Segmented and its Sinogram

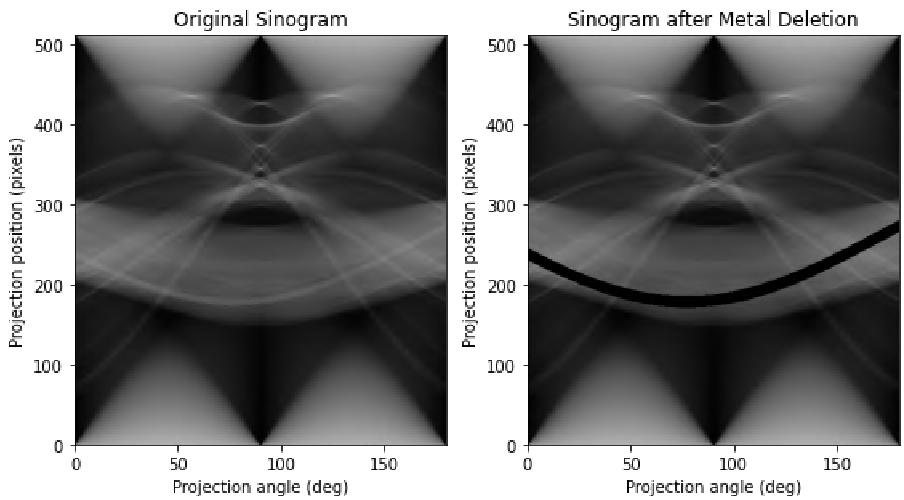

Figure 4.4: Deletion of metal segment from the original sinogram.

4.2 Simulated Dataset Generation

From the dataset obtained from MVR, only 72 slices were feasible for the model (considering only slices with metal artifacts in the region of the teeth). This data was insufficient and produced below-average results after using it for training the model. To overcome this obstacle, metal-contaminated samples were simulated for the purpose of training which can be observed in [4]. To facilitate the simulation, CT slices were taken from patients that presented with no metal artifacts. These were then subject to initial preprocessing steps and converted to their corresponding sinograms(Fig. 4.5). An arbitrary metal-only sinogram was chosen from the set of metal-only sinograms(Fig. 4.6) and deleted from the original sinogram which was then combined with the original input set(Fig. 4.7). The resulting dataset increased from the initial set of 72 samples to a total of 1134 samples.

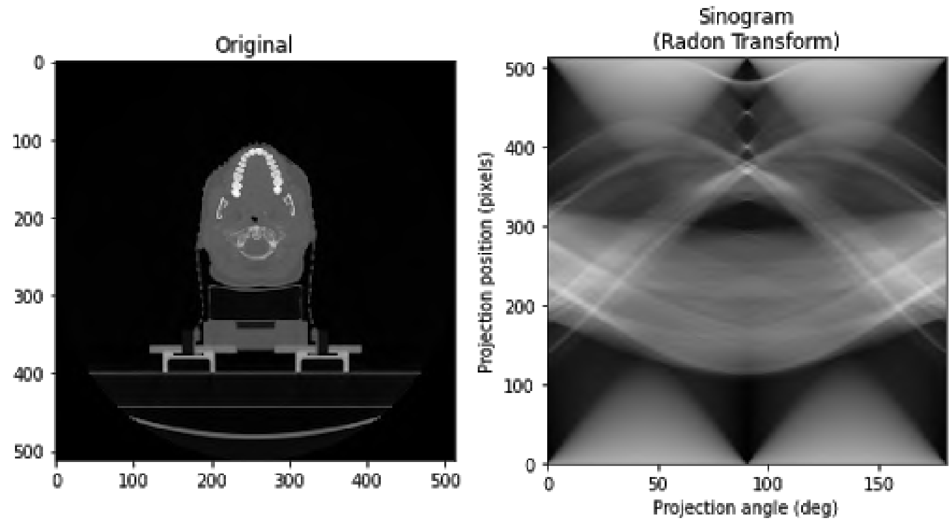

Figure 4.5: Metal-free image and its Sinogram

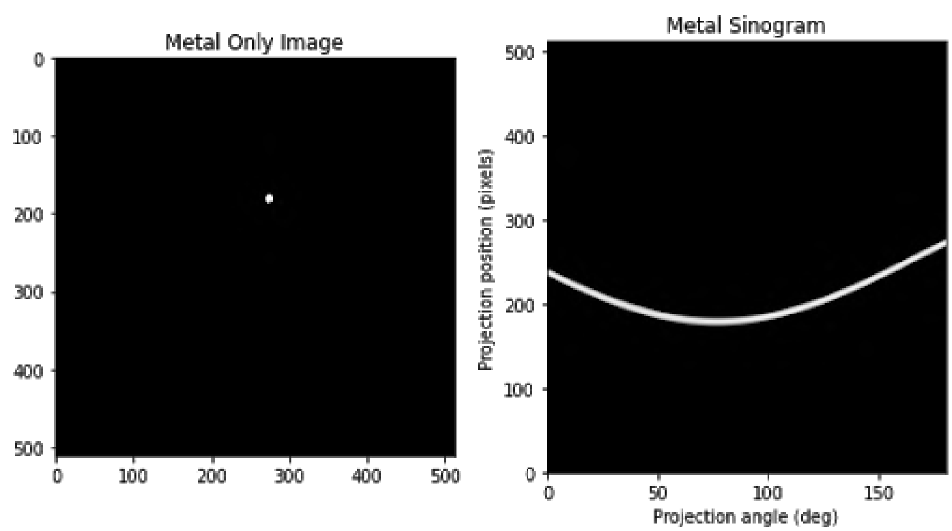

Figure 4.6: Chosen Arbitrary Metal Image and its Sinogram

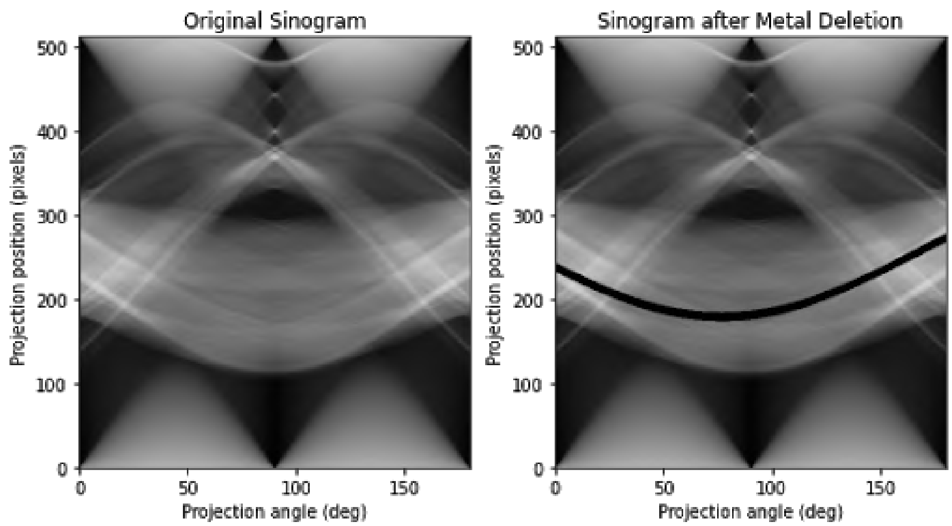

Figure 4.7: Metal-Free(Benchmark) and Metal Deleted Sinogram(Simulated Input)

4.3 Proposed Method I (Using CNN)

The CNN Model makes use of a U-Net architecture taking reference from [6] consisting of four down-sampling layers which is followed by four up-sampling layers. This is illustrated in the Fig. 4.9. Each down-sampling layer consists of applying multiple 2D convolution and batch normalization layers followed by a 2D max pooling function. Each up-sampling consists of applying a concatenation function followed by multiple 2D convolution and batch normalization layers. Skip connections were included to prevent loss of information due to the application of max pooling and convolution in each layer. The loss function used is mean squared error. The loss is calculated by taking the mean of squared differences between target and predicted image.

4.3.1 Training Parameters

Standard rmsprop optimizer with batch size 2 was used for training the model. The standard rmsprop optimizer was used with learning rate 0.01. The model was trained on the dataset for 100 epochs which took around 4 hours to complete. 60% of the dataset was used for training, 20% was used for validation and rest 20% for testing.

4.4 Proposed Method II (Using CGAN)

Conditional Generative Adversarial Network is a deep learning method which is used as a framework to train generative models. It comprises of two neural networks, namely, a generator network and a discriminator network. In this, a conditional setting is applied wherein the generator and discriminator are trained based on some auxiliary information like class labels. Our implementation of the CGAN model has taken reference the pix2pix model available in the Tensorflow documentation (taken from [7]) which was originally used to synthesize high resolution photo-realistic images from semantic label maps.

4.4.1 Generator

The generator fills in the missing data in the metal-deleted sinograms obtained after the preprocessing stage. Our generator makes use of a U-Net architecture which is similar to that used in the CNN model illustrated in Fig. 4.9. The total generator loss is given by:

$$GAN_{loss} + (\lambda * L1_{loss})$$

wherein $\mathrm{Gan}_{\mathrm{loss}}$ is the sigmoid cross entropy loss of the generated images and an array of ones and the $\mathrm{L1}_{\mathrm{loss}}$ is the mean absolute error between the generated and target image.

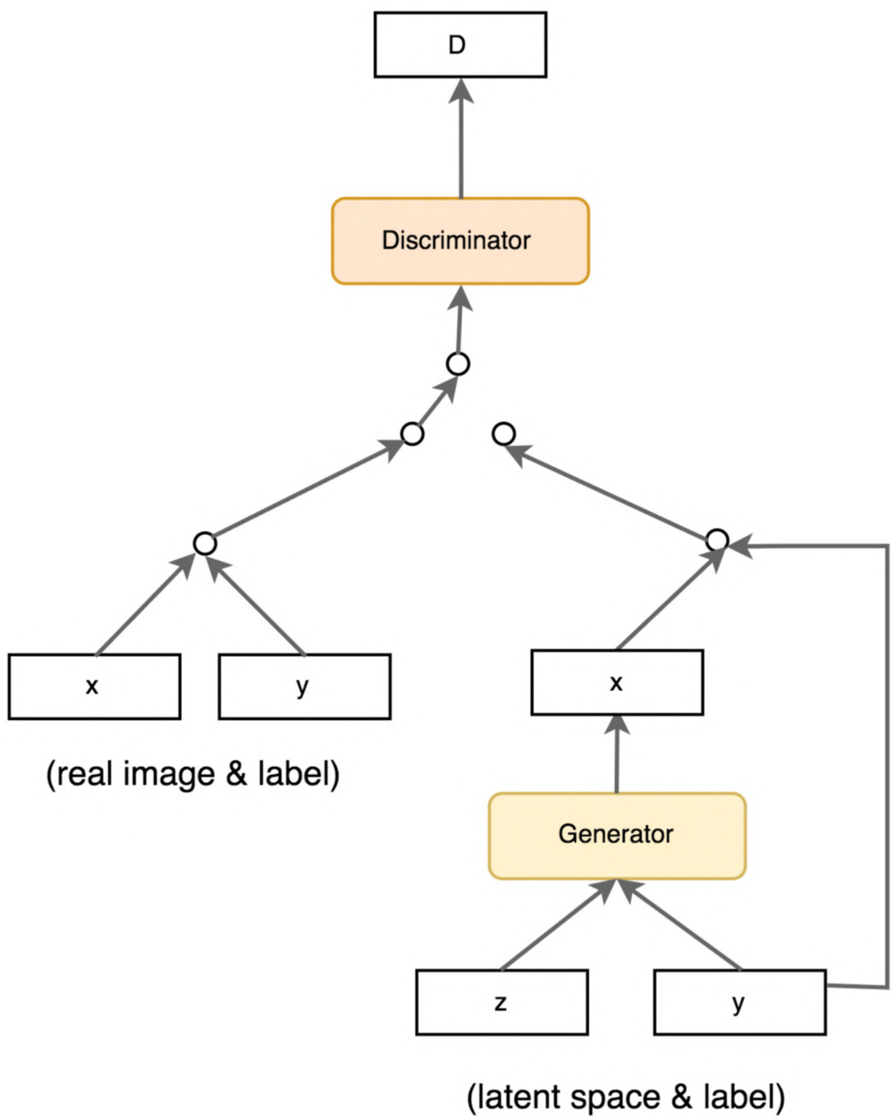

Figure 4.8: Basic GAN Architecture[1]

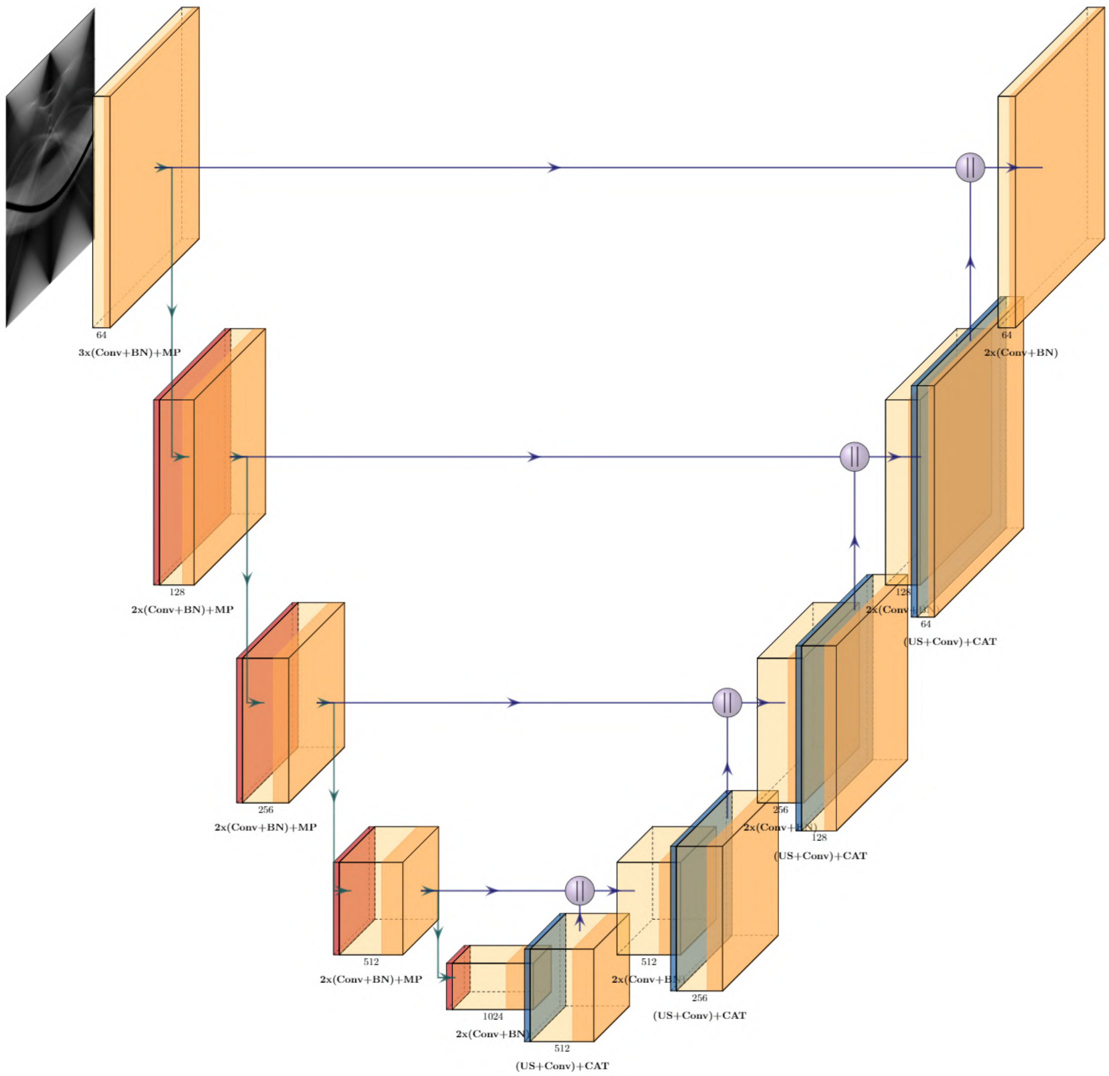

Figure 4.9: U-Net Generator (Conv: Convolution2D, BN: BatchNormalization2D, MP: MaxPool2D, US: UpSampling2D, CAT: Concatenation)

4.4.2 Discriminator

The discriminator is basically a classifier that tries to distinguish between the true sinogram and the sinogram that has been generated and adds in a penalising factor to help train the generator network. It has two inputs - the real sinogram and the generated sinogram. Our discriminator comprises of seven down-sampling layers, each comprising of a 2D convolution layer, a batch normalization layer and a LeakyReLu Layer. This is then followed by a flatten layer and a dense layer as illustrated in Fig. 4.10. The total discriminator loss is given by:

$$Real_{loss} + Generated_{loss}$$

wherein the $\text{Real}_{\text{loss}}$ is the sigmoid cross entropy loss of the real images and an array of ones and the $\text{Generated}_{\text{loss}}$ is the sigmoid cross entropy loss of the generated images and an array of zeros.

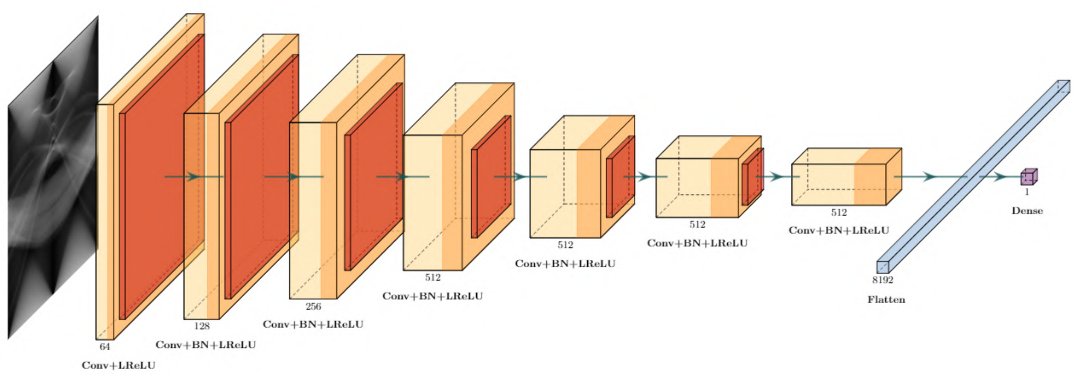

Figure 4.10: Discriminator (Conv: Convolution2D, BN: BatchNormalization, LReLU: LeakyReLU)

4.4.3 Training Parameters

Adam optimizer with batch size 2 was used for training the model. The standard Adam optimizer was used with learning rate of 0.0002 and momentum parameters beta_1 = 0.9, beta = 0.999. Empirically the value of lambda was decided as 10. The model was trained on the dataset for 100 epochs which took around 7 hours to complete. 60% of the dataset was used for training, 20% was used for validation and rest 20% for testing.

4.5 Reconstruction

The sinogram completed is further converted back to image domain using the inverse radon transform. It uses the Filtered Back Projection algorithm to reconstruct the image. Reconstruction angle taken is 180 degree. After converting the sinogram to image, the metal removed in the preprocessing stage is added to the reconstructed image.

4.6 Evaluation Metrics

The metrics used in this study include PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index) as well as MSE (Mean Square Error).

Mean Squared Error: It measures the average squared error between the two images. MSE value between the true image and the predicted image is calculated as:-

$$MSE = \frac{1}{mn} \sum_{0}^{m-1} \sum_{0}^{n-1} \| f(i,j) - g(i,j) \|^2$$

where m and n represent the number of rows and columns of the pixels in the image respectively and f and g represent the 2D matrices of the true image and the predicted image respectively.

Peak Signal to Noise Ratio: It measures the quality of the images. PSNR value between the true image and the predicted image is calculated as:-

$$PSNR = 20 * log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

where $\mathrm{MAX_f}$ represents the maximum pixel value in the true image and MSE represents the mean squared error.

Structural Similarity Index: It measures the structural similarity between the true image and the predicted image. SSIM value between the true image and the predicted image is calculated as:-

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}$$

where μ_x and μ_y represent the average value, σ_x^2 and σ_y^2 represent the variances and σ_{xy} represents the co-variance between the true image and the predicted one. $\mathrm{c_1}$ and $\mathrm{c_2}$ are two variables to stabilize the division with weak denominator.

Chapter 5

Results

5.1 Dataset Acquisition

The medical CT dataset used in this project was collected from MVR Cancer Centre, Kozhikode. It contained data of around 100 patients in DICOM (Digital Imaging and Communications in Medicine) format. Each patient's folder comprised of approximately 200 DICOM slices that represented images from their head to chest. Each slice has 512x512 pixels with a thickness of 2.5mm. This project deals with reducing metal artifacts due to implants in the head slices. So the focus is kept strictly to the head slices, specifically the region around the teeth.

5.2 Implementation Platform

Both the models run on Keras which is Tensorflow's high-level API for building and training deep learning models. The models were initially run on google's colaboratory which uses Nvidia's K80 GPU. Later these models were also tested in the college's (NITC) GPU server remotely which uses Nvidia's V100 GPU details of which are seen in Fig. 5.1.

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 450.36.06    Driver Version: 450.36.06    CUDA Version: 11.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla V100-PCIE...  On   | 00000000:2F:00.0 Off |                    0 |
| N/A   66C    P0   114W / 250W |   9924MiB / 32510MiB |     99%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
```

Figure 5.1: GPU Used and its Metadata

5.3 Results and Discussion

The training performed on both these models with 1134 samples (that include synthesized data as well) indicate that the Conditional Generative Adversarial Network (CGAN) produces better overall scores for all the three metrics. Although both the models work on similar generators that use U-Net architectures, the addition of the discriminator network in the CGAN model has proved to better train the generator network. The added penalty (loss) from the discriminator has been shown to be vital in training the network better and faster. The scores of both the CGAN and CNN models are tabulated and are shown in the tables below.

Completion of Sinogram - The key objective of the proposed model is sinogram completion. The completed sinogram using the CGAN and CNN models are depicted in Fig. 5.2. Each row displays the case of sinogram completion of different sinogram. It is observed that certain regions of sinogram are better completed by the CGAN model compared to CNN as seen in the Fig. 5.2. To prove this quantitatively, the scores of 15 of the sinograms are shown in Table 5.1 and the overall average scores are shown in Table 5.2.

Uncorrected			**CNN**			**CGAN**		
PSNR	**SSIM**	**MSE**	**PSNR**	**SSIM**	**MSE**	**PSNR**	**SSIM**	**MSE**
26.567	0.903	143.35	32.858	0.946	33.673	32.048	0.94	40.573
25.625	0.896	178.085	33.103	0.947	31.825	32.151	0.941	39.624
25.251	0.892	194.097	33.285	0.947	30.521	32.15	0.939	39.635
25.55	0.894	181.185	33.408	0.946	29.664	32.884	0.944	33.47
26.046	0.9	161.613	33.662	0.949	27.982	32.799	0.945	34.136
27.02	0.922	129.157	37.26	0.968	12.221	39.227	0.979	7.769
26.404	0.917	148.829	37.091	0.967	12.704	39.636	0.979	7.07
26.355	0.916	150.498	36.854	0.966	13.417	39.639	0.979	7.066
26.287	0.915	152.886	36.696	0.966	13.914	39.482	0.978	7.327
26.223	0.914	155.174	36.344	0.965	15.09	38.957	0.978	8.268
24.587	0.891	226.162	36.856	0.966	13.412	39.372	0.978	7.514
24.373	0.89	237.585	36.681	0.966	13.965	39.476	0.978	7.336
28.145	0.922	99.677	35.75	0.966	17.303	40.626	0.981	5.63
20.921	0.827	525.971	21.647	0.893	445.045	30.348	0.94	60.014
21.127	0.828	501.669	21.307	0.894	481.239	30.524	0.94	57.631

Table 5.1: Score of 15 completed sinograms using CNN and CGAN

	Uncorrected	**CNN**	**CGAN**
psnr	22.70	29.67	32.42
ssim	0.86	0.93	0.95
mse	387.10	148.6	59.28

Table 5.2: Average scores of completed sinogram using CNN and CGAN

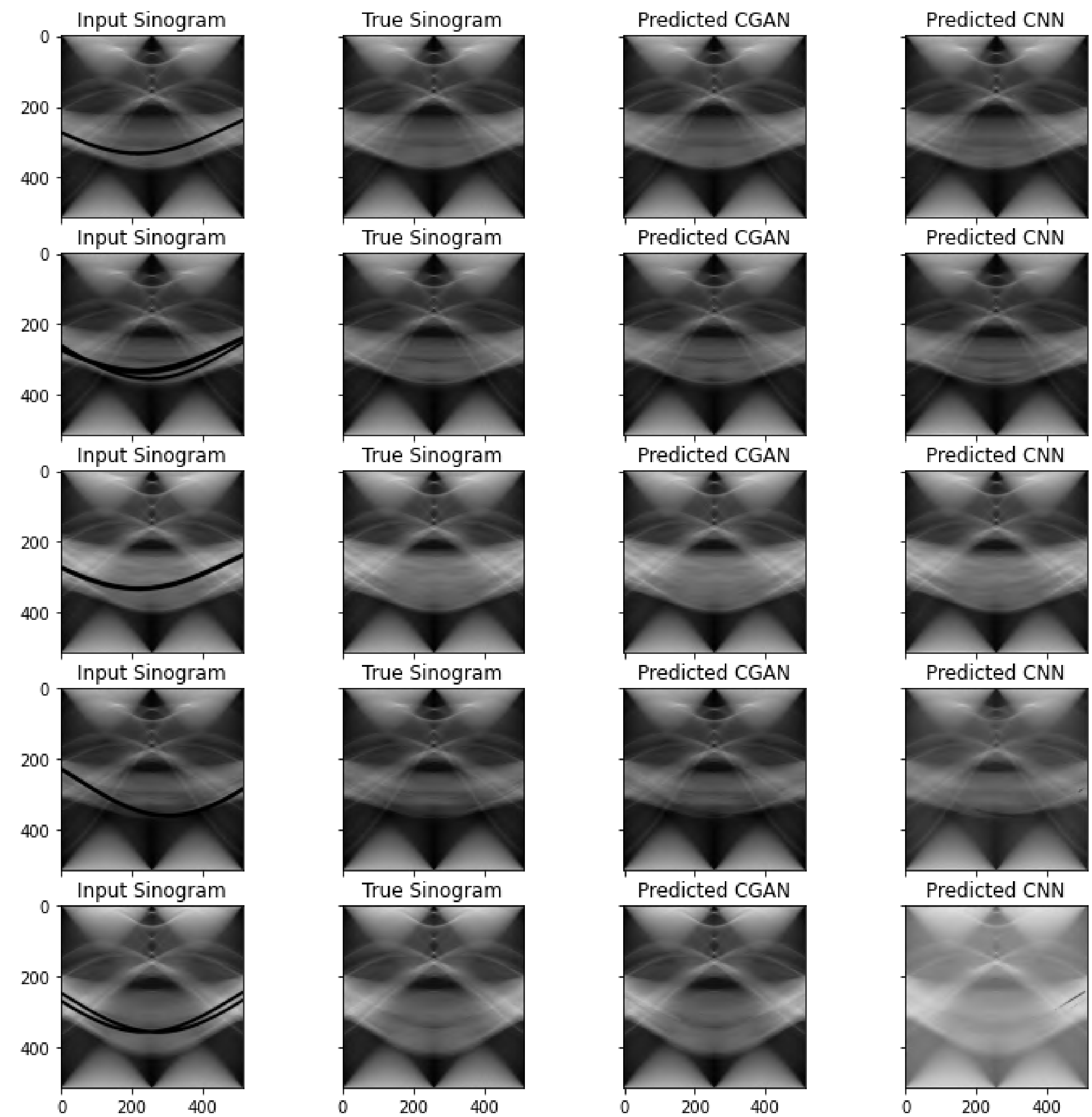

Figure 5.2: Sinogram Completion using CGAN and CNN models

Reconstruction of Completed Sinograms - Fig. 5.3 illustrates the reconstruction of the sinograms after completion using the CNN and CGAN models. The reconstruction is carried out with the help of iradon transform. The first row of the figure shows the original image, the completed sinogram and its reconstruction using CNN and second row depicts the above using CGAN. Fig. 5.4 shows the addition of metal to the image which is reconstructed using iradon and iradon_sart. Fig. 5.5 shows the initial input and final output of the model.
From the results its clear that CGAN model outperforms the CNN model and produces better output images. In CNN model the loss function is explicitly fixed due to which no changes can be reflected back to it during the training phase. Meanwhile,in CGAN model the generator uses the discriminator as the loss function, meaning that the loss function for the generator is implicit and learned during training phase. This is the key factor behind the success of the CGAN model producing better results than the CNN model.

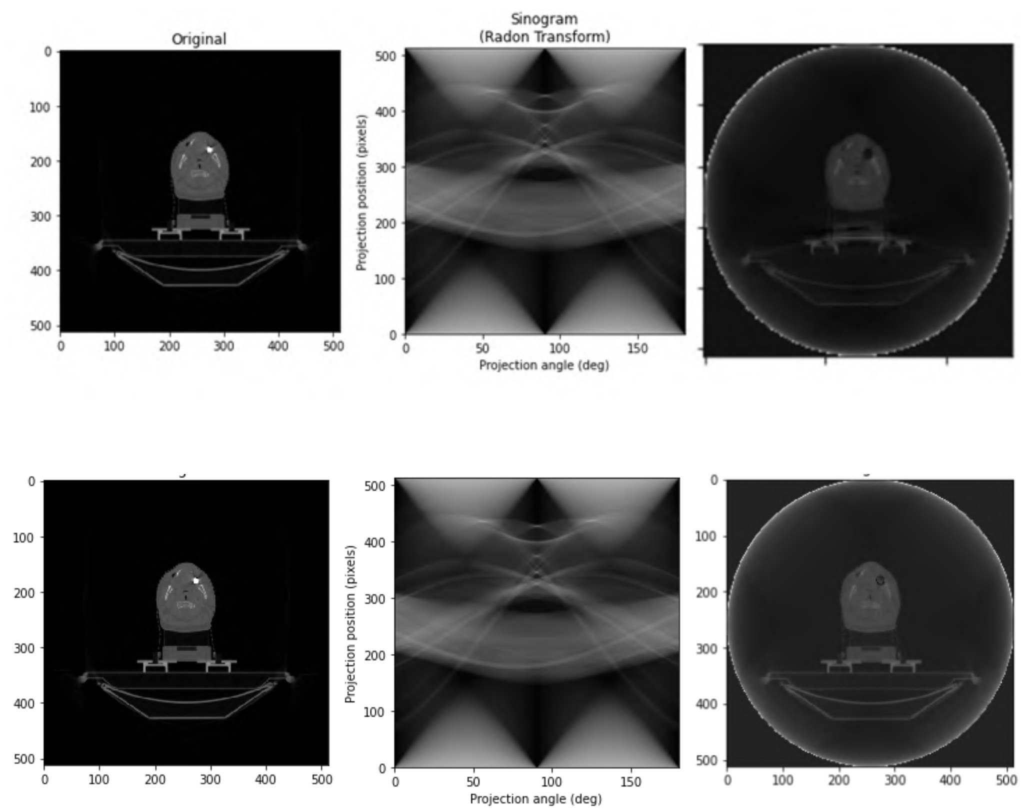

Figure 5.3: Reconstruction of Sinogram using iradon(CNN and CGAN)

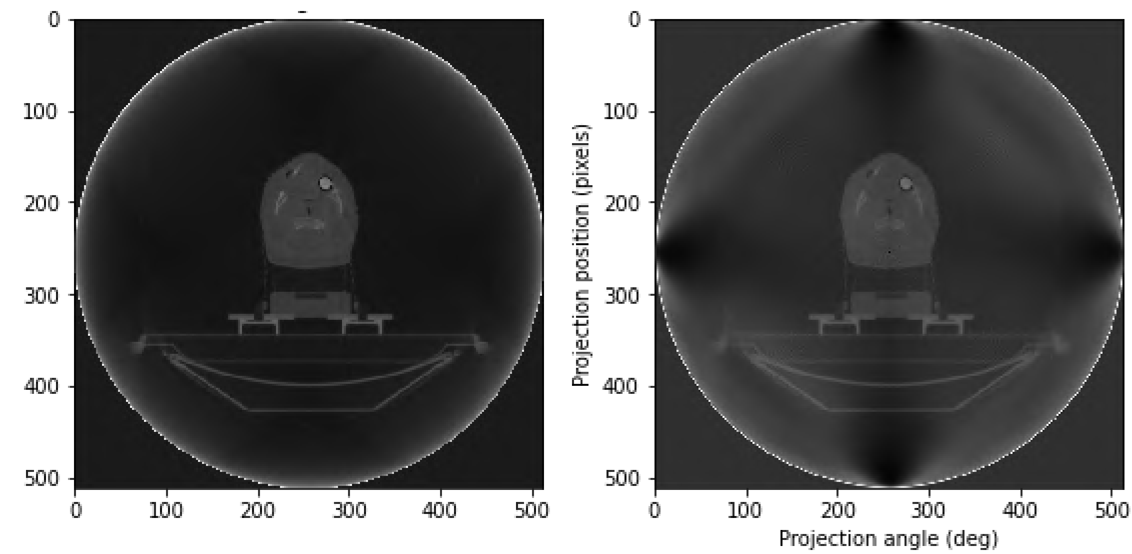

Figure 5.4: Addition of Metal to Reconstructed Image

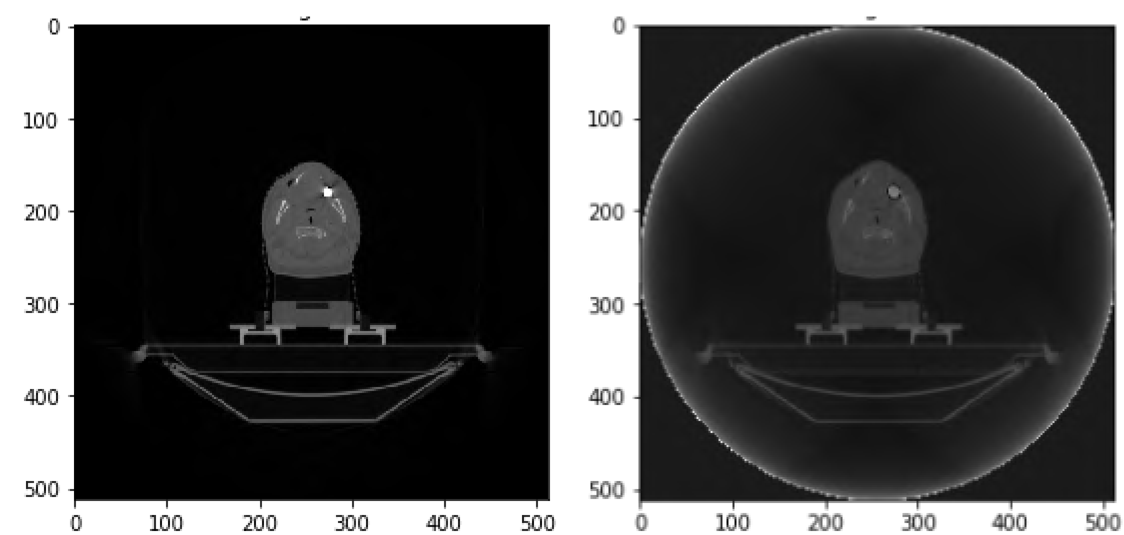

Figure 5.5: Input Image and Output Image

Chapter 6

Conclusion and Future work

CT scans are one of the most fundamental tests used in the fields of security and medical diagnosis. Metal artifacts pose a serious threat to obtain accurate interpretations. Reduction of metal artifacts still remains as a interesting challenge in this field and research has suggested that employing deep learning techniques can be a viable solution to this problem. Through this project, a comparative analysis of two advanced deep learning techniques, a standard CNN approach and a CGAN approach, have been carried out. Results indicate that the CGAN model performed better by generating images with higher quality as well as a higher overall accuracy. The main objective was to release an open-source framework that can be developed further in the future. The source code of the work done can be found in `https://github.com/akarshjoice/Major-Project`
To overcome the difficulties faced during the training stage, efforts will be made towards accumulating a larger medical CT dataset to achieve an improved version of the current model. Furthermore, as an extension to this project, a DCGAN (Deep Convolutional Generative Adversarial Network) model would also be implemented to perform metal artifact reduction, which is a popular and successful network design for GAN that composes of convolution layers without max pooling or fully-connected layers.

References

[1] Jonathan Hui, *GAN—CGAN and InfoGAN (using labels to improve GAN)*, 2018. https://medium.com/@jonathan_hui/gan-cgan-infogan-using-labels-to-improve-gan-8ba4de5f9c3d.

[2] Y. Zhang and H. Yu, "Convolutional neural network based metal artifact reduction in x-ray computed tomography," *IEEE Transactions on Medical Imaging*, vol. 37, no. 6, pp. 1370–1381, 2018.

[3] M. U. Ghani and W. C. Karl, "Deep learning based sinogram correction for metal artifact reduction," *Electronic Imaging*, pp. 4721–4728, 2018.

[4] M. U. Ghani and W. C. Karl, "Fast enhanced ct metal artifact reduction using data domain deep learning," *IEEE Transactions on Computational Imaging*, vol. 6, pp. 181–193, 2020.

[5] Lars Gjesteby, Qingsong Yang, Yan Xi, Bernhard Claus, Yannan Jin, Bruno De Man, and Ge Wang, "Reducing metal streak artifacts in ct images via deep learning," *The 14th International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine*, 2017.

[6] Wang J, Liang J, Cheng J, Guo Y, and Zeng L, "Deep learning based image reconstruction algorithm for limited-angle translational computed tomography," *PLoS One*, vol. 15, p. e0226963, 2020.

[7] P. Isola, J. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 5967–5976, 2017.

[8] F. Edward Boas and Dominik Fleischmann, "Ct artifacts: Causes and reduction techniques," *Imaging in Medicine*, vol. 4, 2012.