UCSD Electrical & Computer Engineering

ECE 228

Deep Convolution Neural Network for CT-Image Reconstruction

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Abstract

- Computed Tomography (CT) imaging is an important tool used in diagnosing and evaluating patients.
- In order to generate CT images, contemporary methods evaluate a set of X-ray signals generated at different orientation and compute an image from the tomographic information.
- Deep convolution neural networks have the potential to replace conventional analytic solution for CT imaging while using sparser sets of X-ray signals and thus reducing the amount of radiation exposure for patients.
- We extend this problem towards the specific task of generating CT chest images of Covid-19 patients.

Approach Towards Sparse Imaging

Goal: Be able to generate computed tomography (CT) images using less information than conventional modern-day methods.

Approach: Train a deep convolution neural network (CNN) with the following steps:

- Preprocesses raw CT images from dataset in order to remove unnecessary noise from the image.
- Convert preprocessed images into sonograms using radon transformation functions.
- Extract a limited number back projected slice images.
- Train deep CNN model using the set of back projected slice images as an input.

Questions posed:

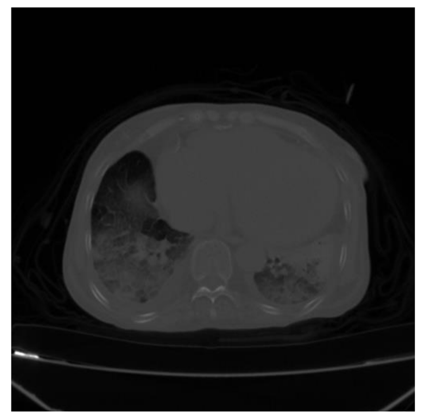
- How does sparsity of input data affect model training and performance, especially with consideration Nyquist theorem?

Data set background & Data Preprocessing

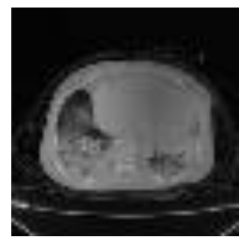
The raw dataset was acquired from Harvard's Covid-19 CT Chest Scans Dataset [1], which contained a collection of CT chest scans of patients with covid. For each patient, approximately 500 – 700 images were collected with the whole dataset containing images from over 1000 different patients.

Preprocessing of the raw dataset included the following steps:

- Resizing the image from the original 512 x 512 image size.
- Applying a series of limited erosion and dilation image processing.
- Applying a Contrast Limited AHE adaptive histogram equalization to sharpen contours of image.



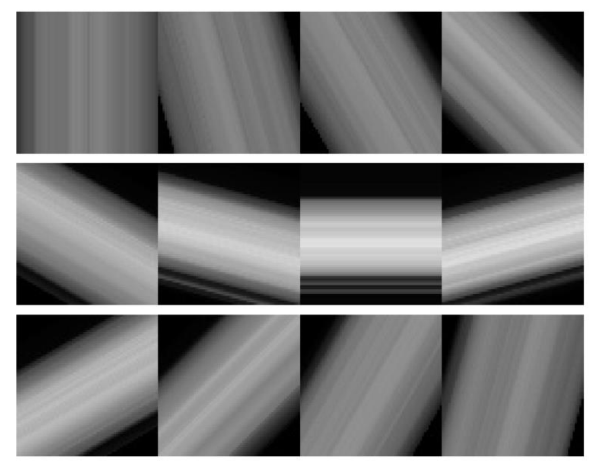
Original Image



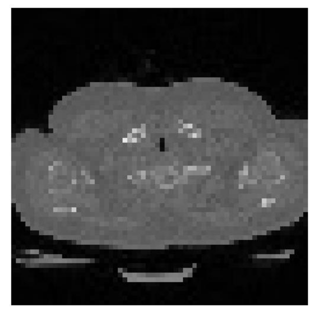
Processed Image

Radon Transformation

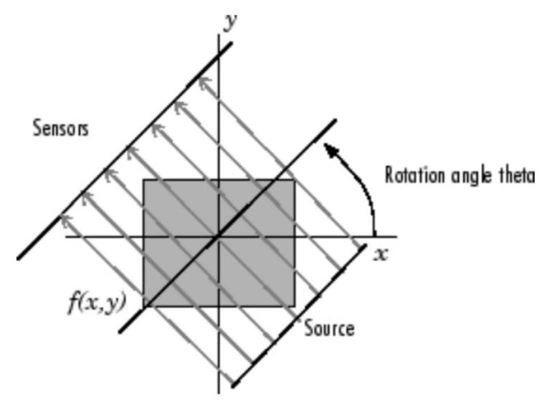
The Radon transform function computes the projections of an image matrix along a specified direction. For a 2D image, the projections of the image data found via radon transform can be considered a set of line integrals of pixel intensities along parallel paths. By sampling axes at various orientations, a set of radon transforms can be combined to form a sinogram image. The signal intensities for each projection can be cast as parallel lines of uniform intensities along the direction of the original signal. The resulting images with parallel lines of uniform intensities are called back-projected slice sinogram images. Collectively, these back-projected images are useful since they represent spatial-based information in a non-spatially dependent way. This makes back-project images a convenient input for a convolution neural network style model.



Generated Slice Projection

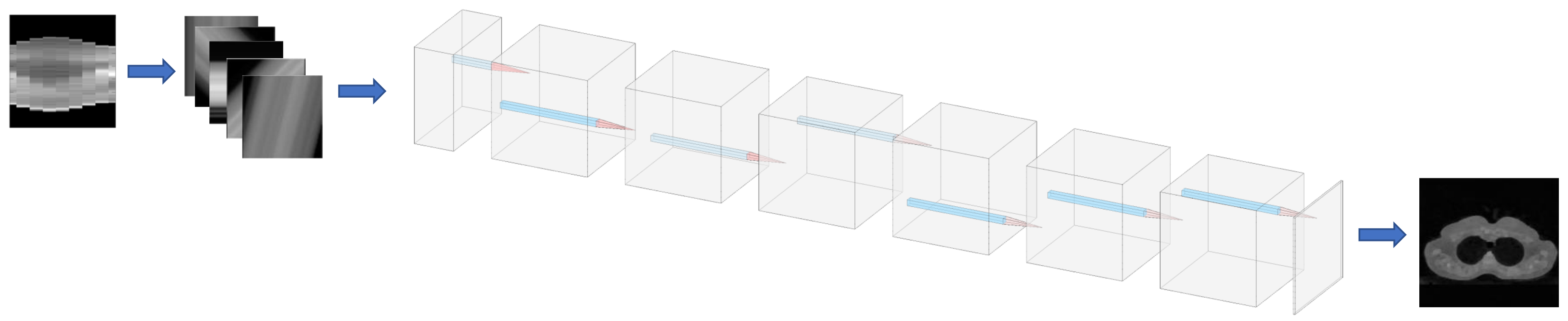


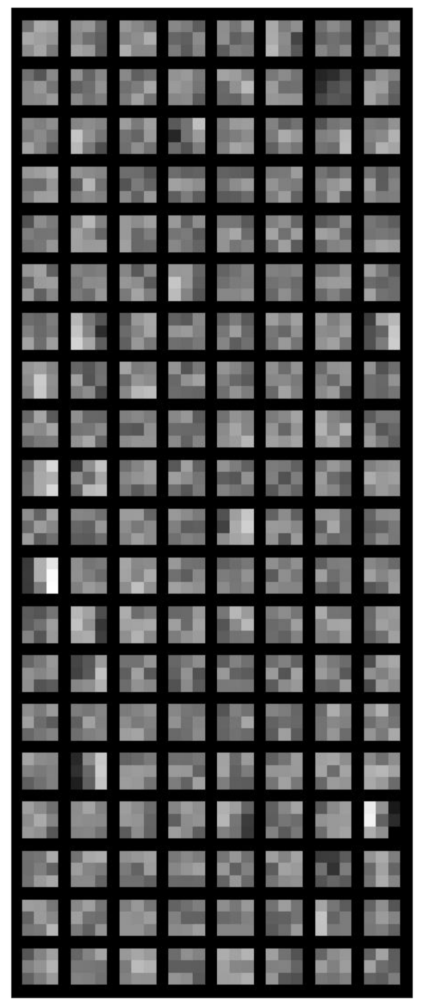
Truth Image



Generating Slice Images

Architecture



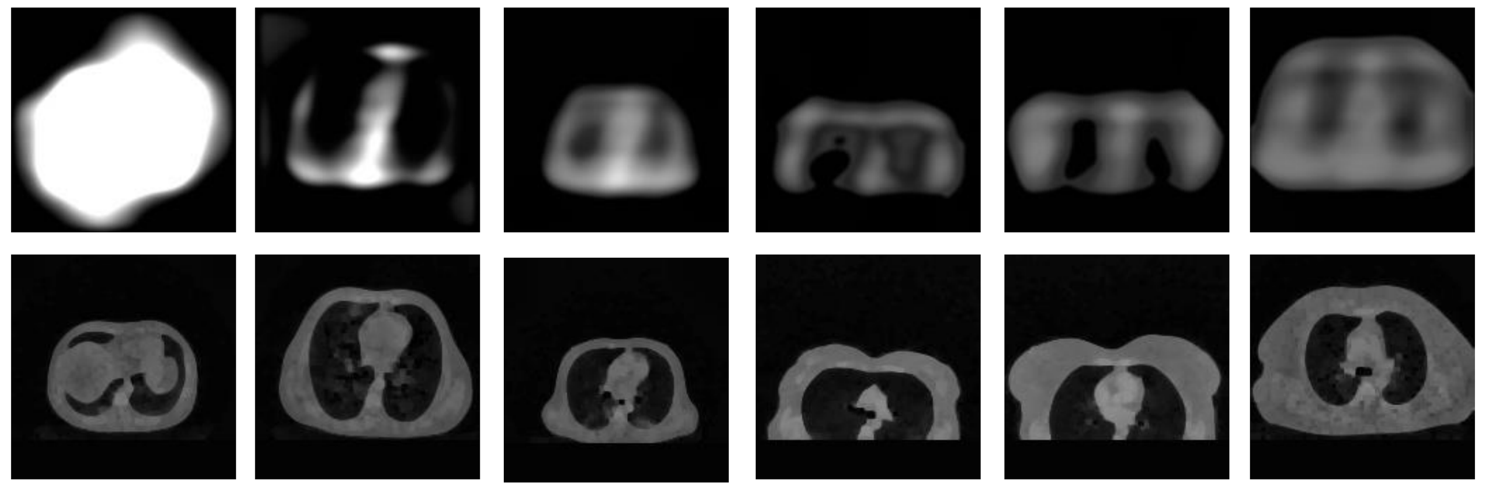


The network architecture used for this project follows a similar structure to [3]. The layers follow:

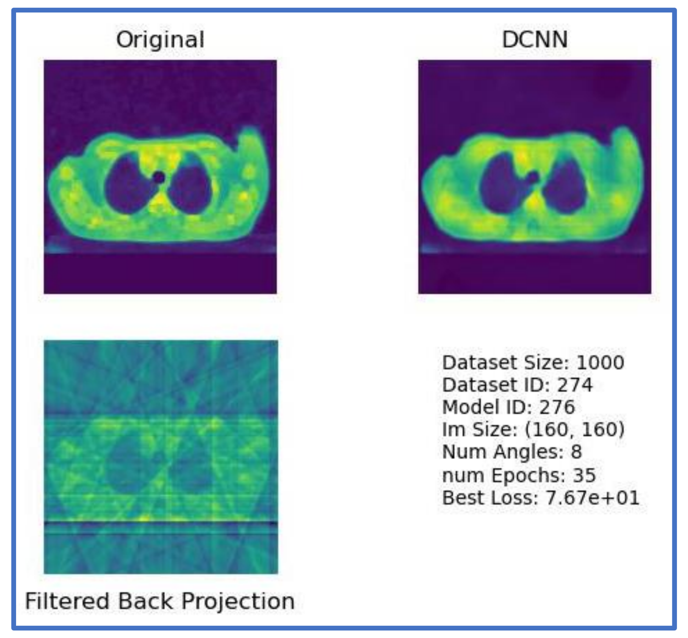
1. (Conv2d, ReLU)
2. (Conv2d, BatchNorm2d, ReLU) x15
3. (Conv2d)

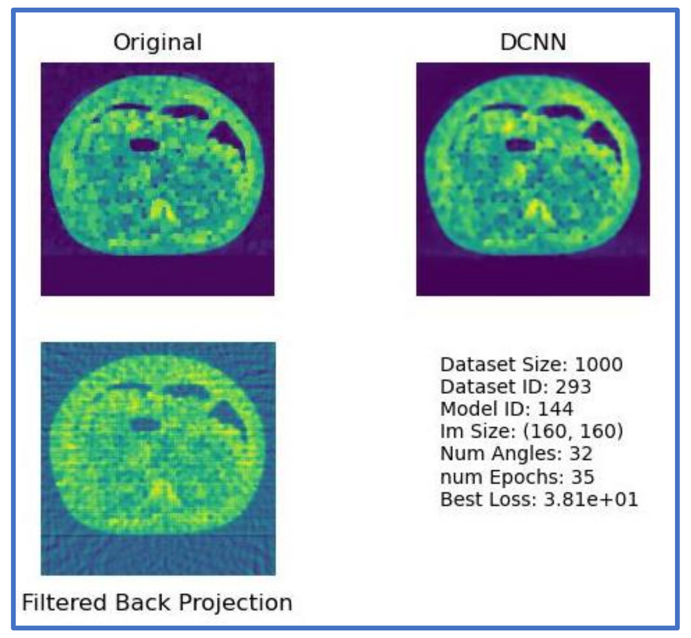
The left figure is a visualization of the first layer's weights. There are 160 (3x3) filters in total.

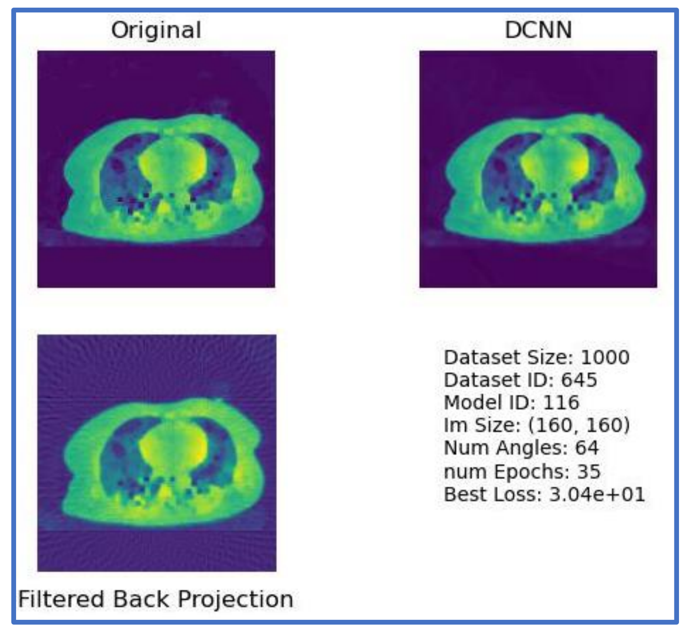
Below is a showcase of the model's performance after 1,2,3..,6 epochs and their corresponding truth image.

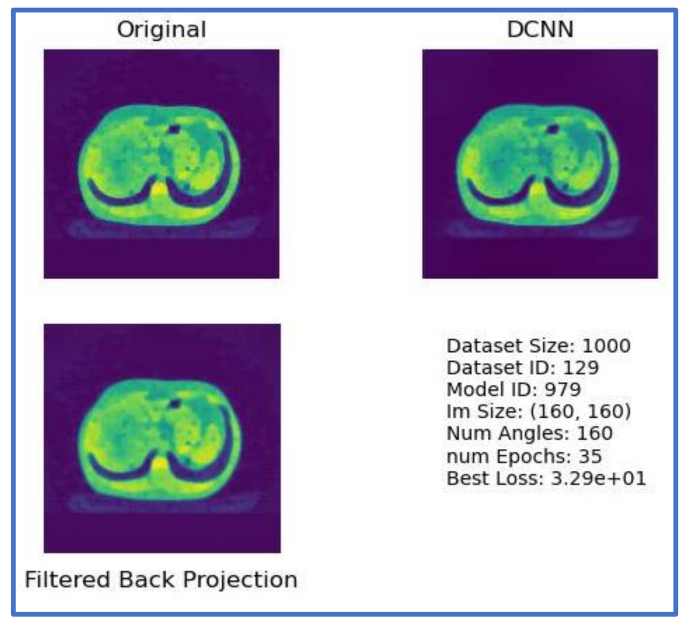


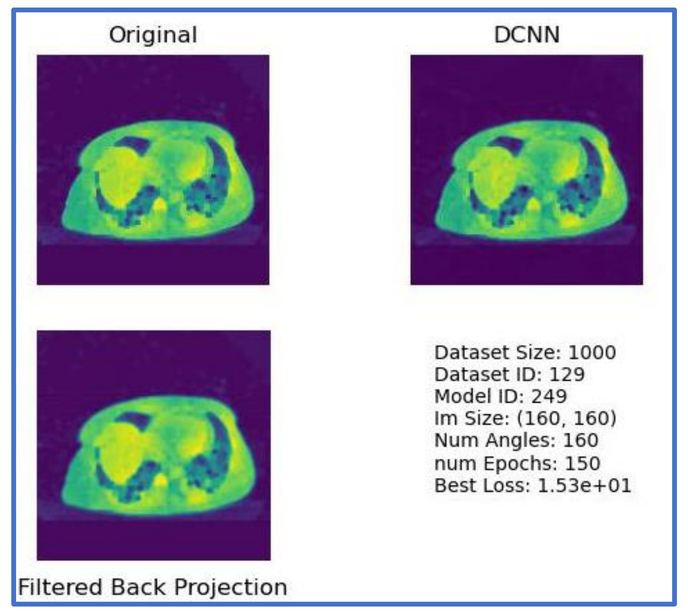
Results

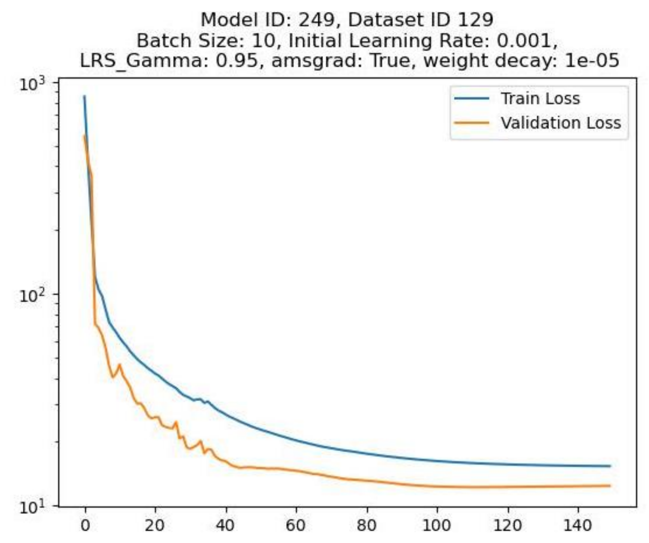












Conclusion & Future Work

Our work shows that we were successful in breaking the Nyquist rate limit in contemporary CT image processing. This has the implication a DCNN can potentially reduce the exposure of harmful X-ray radiation to patients in CT. Future work with this model is experimenting with less preprocessing, larger images, and a study of the effect of noise.

References

[1] Jonas Adler and Ozan Öktem. Learned primal-dual reconstruction. IEEE Transactions on75
Medical Imaging, 37(6):1322–1332, 2018.76

[2] Sayyed Mostafa Mostafavi. COVID19-CT-Dataset: An Open-Access Chest CT Image Repository77
of 1000+ Patients with Confirmed COVID-19 Diagnosis, 2021.78

[3] Dong Hye Ye, Gregery T. Buzzard, Max Ruby, and Charles A. Bouman. Deep back projection79
for sparse-view ct reconstruction, 2018