# Optimizing Projection Radiography with Machine Learning

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## Abstract

Projection radiography is one of the most popular imaging modalities on the market as it is relatively cheap, widely available, and can be used for many different applications. Here I investigate two physical parameters of projection radiography, Compton scatter and exposure time, and apply the physical parameters in the augmentation of data to investigate their effects on the binary classification of chest x-rays for healthy individuals and patients with either bacterial or viral pneumonia. I find that the augmentation of the training and testing data has little effect on the accuracy of the models, and this lead to the further investigation of training these physical layers using a TensorFlow Eager model. Due to time and resource constraints I was unable to achieve successful training of the physical parameters, but I do propose future steps to investigate these parameters further.

## 1 Introduction

Projection radiography refers to the most common form of imaging that employs the use of x-ray electromagnetic radiation. The x-rays for projection radiography are generated in an x-ray tube, which consists of an anode and cathode that are housed by a lead based enclosure. Within the cathode is a small tungsten wire, and when the x-ray tube is working a current runs through this wire creating resistance, and in return it emits electrons into the x-ray tube. These are directed at the anode through a potential difference inside the tube, and when the electrons strike the anode, different interactions occur on the surface of the anode.

The interactions that we are interested in are the production of characteristic and bremsstrahlung x-rays, which produce the electromagnetic radiation used in projection radiography. When these x-rays are produced they can be directed at a person for the use in an x-ray or CT scan. When these x-ray photons enter a person's body they either pass through the person's tissue and hit the x-ray detector, hit the nucleus of an atom and get absorbed by the person's tissue, or they hit the electron cloud an atom in a person's body and send that electron off in a separate path causing Compton scatter [1].

This paper will investigate the effects of these interactions and the resulting effect that these x-ray parameters have on the accuracy of a binary classification convolutional neural network. In particular this paper will investigate whether the x-ray's exposure time and whether the occurrence of Compton scatter play a significant role in the x-ray classification of chest x-rays of healthy individuals and patients with pneumonia.

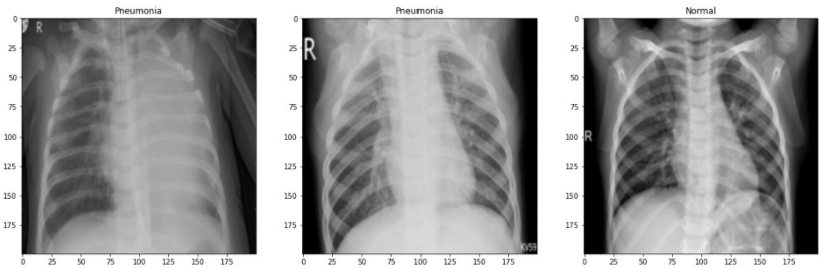


Figure 1: Sample chest x-ray scans from the dataset

## 2 Related Work

The use of AI and machine learning has exploded over the past few decades with advances and optimizations of current models coming out at an exponential rate. Machine learning can be used for classification, segmentation, and object detection, and has seen applications in all medical imaging modalities.

One main use of medical imaging is to assist or check a medical professional when making a diagnosis. Chest x-rays are the most common imaging modality used for the diagnosis of pneumonia, but they are still sometimes difficult to read, even for a trained medical professional. That is why deep learning models like ResNet18, InceptionV3 and DenseNet121 are being applied to the diagnosis of pneumonia in chest x-rays [1].

Machine learning, however, is no longer solely used for the analysis of images, it is now being used to optimize the physical parameters of the imaging hardware itself. From reducing the required gadolinium dose in contrast-enhanced MRI to improving the attenuation correction for PET-MRI scans, machine learning can be used unlock efficiencies in imaging systems that we didn't know were there [3]. In relation to my project, CNNs have been shown to boost x-ray tomography signal acquisition by a factor of 10, enabling the use of low dose x-rays in x-ray tomography [4].

## 3 Methods

### 3.1 Data Processing

The data that I used for this project came from a study on convolutional neural networks performed by Kermany et al. This dataset consists of 5,863 chest x-rays and labels in two categories, images of patients who's health is normal and images of patients who have pneumonia. The patients with pneumonia can have either bacterial or viral pneumonia. The data is contained in three folders for training, validation, and testing data and within those folders the images are kept in either a folder labeled 'NORMAL' or 'PNEUMONIA'. I loaded the dataset and cropped all of the images to a uniform size of (200 x 200 pixels) as the dimensions of the images in the dataset varied. The normal and pneumonia data and labels are appended to their respective train, test, and validation lists for use later in the project. Fig. 1 shows sample images from the training dataset [5].

### 3.2 Creating a Basic Model

The first model built for this paper is a simple sequential CNN which is diagrammed in Fig. 2. This model was design for simplicity and ease of implementation due to the short time frame of this project. This model consists of four convolutional layers, the second and fourth of which have strides of two to simulate a max pooling layer. The kernel size used in these layers is a small (3 x 3) kernel. The smaller sized kernel is used because smaller details in the chest x-rays are important in the classification problem.

After the convolution layers is a dense layer which is meant to serve as a fully connected layer. I add a dropout after this dense layer to reduce the likelihood of the model over fitting due to the large size of the training data. The final dense layer brings the size of the fully connected layers down to 1 and uses a sigmoid activation function to produce either a 0 for normal or 1 for pneumonia. Due to the

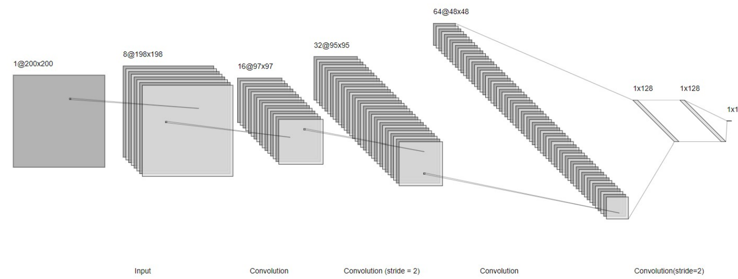


Figure 2: The CNN model used in this paper

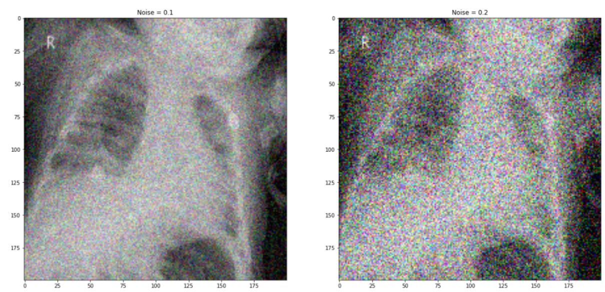


Figure 3: Compton scatter is simulated

simplicity of the model, it did not take long to train, so I was able to train it for 12 epochs which led to accurate data.

This initial model is meant to serve as a benchmark for the later applications of Compton scatter and varying exposure time. Because of this, it is trained with the chest x-ray images as is without any data augmentation. This will possibly effect the test accuracy, but it is not meant to serve as a test of the physical layers yet.

### 3.3 Applying Compton Scatter

This stage of the paper is where the physical parameters of projection radiography come into play. In this section the images are subjected to Gaussian noise which is meant to represent the stray electrons that hit the x-ray detector during scan acquisition due to Compton scatter. To do this, I compare the accuracy from the previous section to the accuracy of the same model but now trained with data containing Gaussian noise. The noise values that I chose for this section both have a mean of 0 with one having a standard deviation of 0.1 and one having a standard deviation of 0.2. Fig. 3 gives a representation of what an image looks like with Gaussian noise applied. It would have been good to investigate a wider range of noises for this section but when I would try to add more datasets with different noise parameters the available RAM for my session would be maxed out.

### 3.4 Changing the Exposure Amount

After training a model using Compton scatter, I moved to investigating the effect that exposure time has on model classification. When the exposure time of an x-ray is increased, the number of photons that hit the detector is greater and thus the intensity of the image is larger. The opposite happens when the exposure time is decreased. To model the effect of classification I multiplied all of the values of the x-ray scans by constants to simulate changes in intensities. The constants that I chose are 2 for a longer exposure time and 0.5 for a shorter exposure time. Fig. 4 gives a representation of sample images augmented by different exposure times. Similarly to the section above I trained the model using using the augmented x-ray datasets and compared the accuracy which is discussed below.

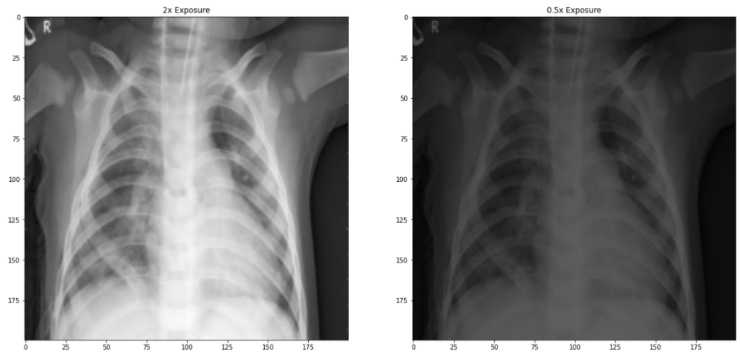


Figure 4: Different exposure times simulated

### 3.5 Creating a Model with TensorFlow Eager

For this last part of the methods I built a new model but this time instead of using the keras based graph system that I used for the previous three sections I used the TensorFlow Eager functionality that gives a user more freedom of the variables being trained. The purpose of this section is to establish trainable physical parameters that can be optimized by the machine learning model and hopefully be used to make a physical change to affect the exposure time or Compton scatter.

The first step of applying this new model was to again train it on the original chest x-ray data. After this I created a function that took batches of the images as input and performed operations on the batches to simulate physical parameters. This physical function had a trainable illumination phase that was established using a tf.Variable and represented the resulting x-ray intensity due to the exposure time. This function also had a trainable variable for the noise of the image and there was also a trainable circular mask that represented an x-ray collameter. This function returned the batches of images having been augmented by physical variables and these batches were then used for training.

## 4 Results

The results for the accuracy and loss of the standalone model from section 3.2 are plotted along with the models trained with augmented data in sections 3.3 and 3.4. As you can see in Fig. 5 and Fig. 6, the loss and accuracy values were all very close, with the original model being slightly higher than the other two models in both cases.

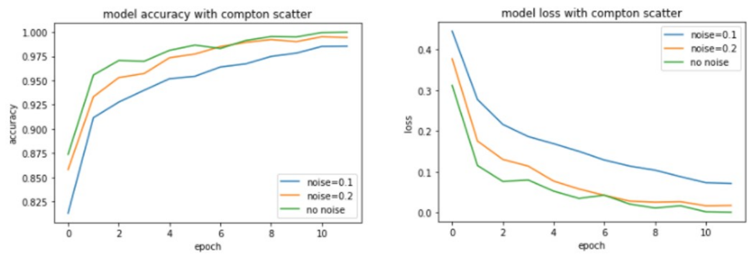


Figure 5: Accuracy and loss plots for Compton scatter

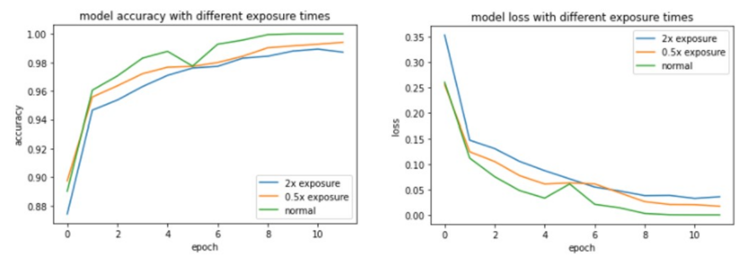


Figure 6: Accuracy and loss plots for exposure time

The TensorFlow Eager model also performed quite well in it's standalone training. The application of the trainable physical parameters using the Eager model was unsuccessful. Upon training of the physical layers, the output of the model would remain at the same accuracy for the duration of the training process.

## 5 Discussion

The lack of difference in accuracy for the augmented images is promising for future applications of machine learning for the optimization of physical parameters. The fact that the accuracy of the models in sections 3.3 and 3.4 were at most 1.6 % worse than the model in section 3.2 shows that machine learning an act as a solution to inopportune physical parameters.

The application of the trainable physical parameters would have been the highlight of this project had they worked. The implementation of the physical parameters was rushed due to time constraints and not enough focus was placed on finishing this portion of the project. Possible reasons for the failure of the physical parameters was the improper use of the tf.Variable() trainable variables in the physical layer or the wrong loss function. The use of noise to represent Compton scatter also would not have had an effect on the outcome had it worked, as the noise would just be optimized to zero. Possibly instead of using Gaussian noise as a representation of Compton scatter I should have instead used a blur kernel.

### Acknowledgments

I would like to thank Dr. Horstmeyer for the great year. I thought that this class was a fun and interesting exposure to the world of machine learning. I learned a lot about concepts that I have never learned about before. I would also like to thank Colin Cooke for leading discussions and providing help many times during the course of this semester.

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