# A Generative Adversarial Network for Image Reconstruction

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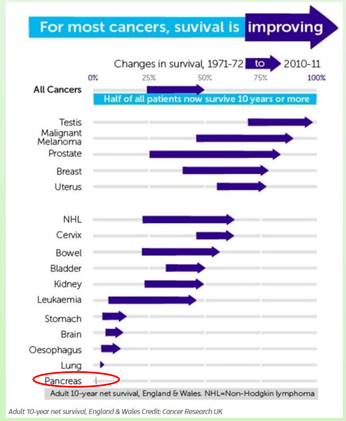
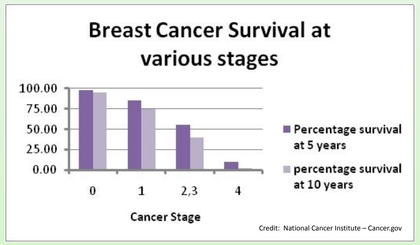
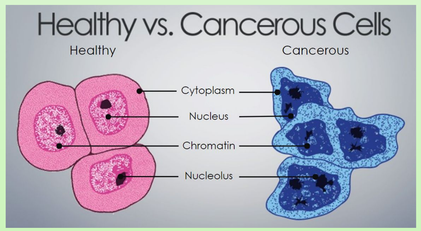
## Introduction

Survival rates for most cancers have increased steadily over the past few decades as new technologies have led to better treatment outcomes. However, this process often relies heavily on the detection of cancer in its earliest stages, before symptoms occur or a tumor is visible in a CT or MR image. This is particularly true for diseases such as pancreatic cancer that exhibit almost no symptoms until very late stages and have extremely low survival rates as a result. Even some commonly treatable diseases, such as breast cancer, become far more problematic in later stages. As such, any efforts to improve cancer treatment further will inevitably require the detection of so-called micro-cancer, small clusters of cancer cells that are often manifest as metastatic circulating tumor cells (CTCs). Fortunately, cancerous cells typically exhibit a morphology that is highly distinct from healthy cells, allowing their detection using visible and infrared light that interacts strongly with objects on the scale of a few microns (due to a wavelength of ~500-900 nm).

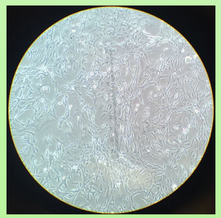


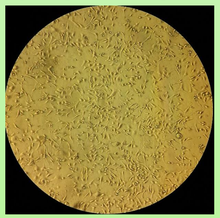



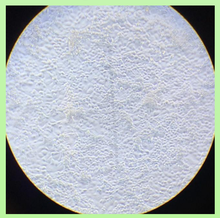



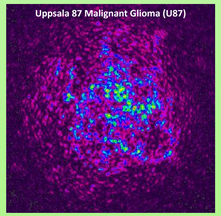

## Prior Work

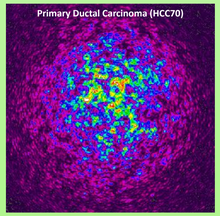
Over the past few years, our group has been culturing and imaging several different cancer cell lines, including Malignant Glioma (U-87), Primary Ductal Carcinoma (HCC-70), and Epithelioid Carcinoma (Panc-1). These cell lines have been photographed using an optical microscope and their characteristic diffraction patterns, produced by near-infrared (854 nm) and red (532 nm) diode lasers, have been collected using an optical beam profiler (LBP2; Newport, Irvine, CA).

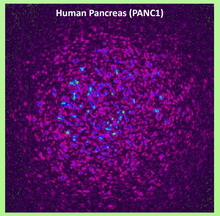






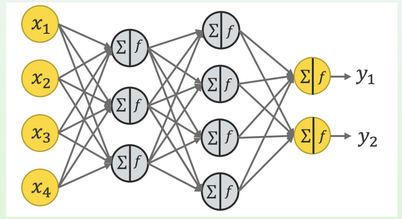


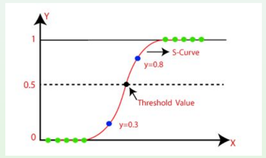



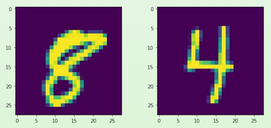




## Machine Learning

Machine learning involves making predictions based on patterns learned from pre-existing data. It is an exciting new field that has already found a large variety of applications in research. We intend to use machine learning for better image reconstruction in our research.

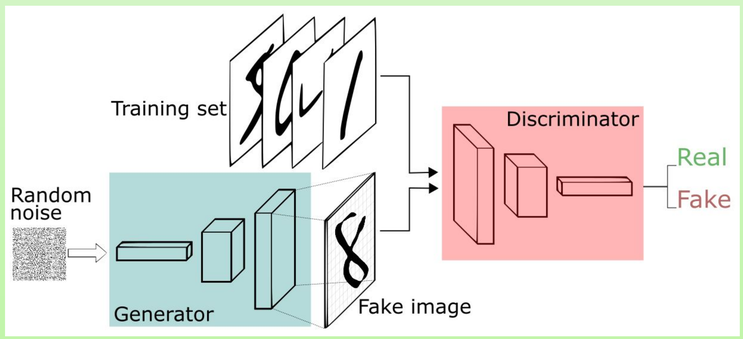


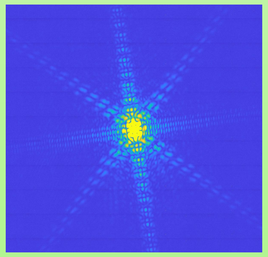



## Generative Adversarial Networks

Generative adversarial networks (GANs) are a new type of machine learning that we intend to use for image reconstruction. These networks are capable of producing new content by identifying patterns in existing data and calculating probability distributions for the values of output pixels. After a random input sample is provided the generator modifies pixel values based on this probability distribution. The resulting image is then fed to the discriminator, which serves as a classification network used to predict whether the image is real or fake. Over time, the generator becomes more adept at producing fakes, while the discriminator is better able to identify fakes.




## Diffraction Patterns



A diffraction pattern collected from an Air Force target card in the CIBEAM lab.

Diffraction patterns are formed in the far field by light that has scattered from an object. These patterns are the 2D Fourier transform of the target and, due to the interference information present in the fringes, include both amplitude and phase information. This can be used to determine the object's size, shape, refractive index, density, and orientation. For the purpose of our research, laser light will be used to create a diffraction pattern of objects at the cellular level with the goal of reliable imaging for cancer cells at spatial resolutions currently inaccessible to conventional microscopes.

## Spatial Frequencies

Spatial frequencies describe the change of a signal as a function of space. In our case, we are attempting to gather this information for the purpose of image reconstruction. As such, higher spatial frequencies will correspond to higher image resolution, with more pixels representing each part of the image. This will allow a visualization of smaller intracellular structures (e.g., mitochondria) that have been linked with early malignancy but are typically beyond the resolving power of conventional optical microscopes. The hybrid input-output algorithm, which involves taking inverse 2D Fourier transforms in reciprocal space, will be used to reconstruct diffraction data collected by a detector.

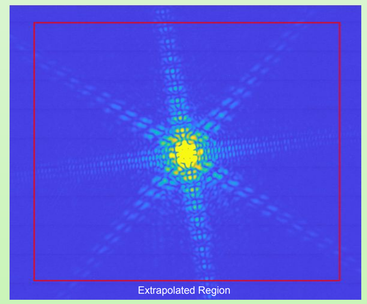
Diffraction data will primarily be acquired using a laser mounted vertically above a horizontal translation stage. Light scattered at high angles is typically noisy and faint, making data collection difficult. As such, the GAN will be used to extrapolate the values of pixels beyond the edge of the detector window (denoted by the red box in the figure below). This will help us to reconstruct the image with higher spatial resolution.

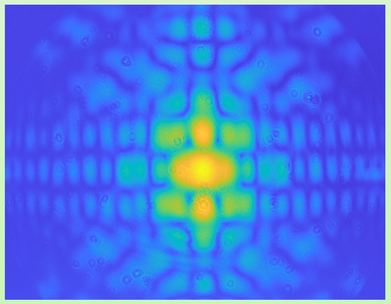
$$f[m,n]=\sum_{k=0}^{M-1}\sum_{l=0}^{N-1}F[k,l]e^{j2\pi\left(\frac{k}{M}m+\frac{l}{N}n\right)}$$

Inverse 2D Discrete Fourier Transform

$$F[k,l]=\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}f[m,n]e^{-j2\pi\left(\frac{k}{M}m+\frac{l}{N}n\right)}$$

2D Discrete Fourier Transform

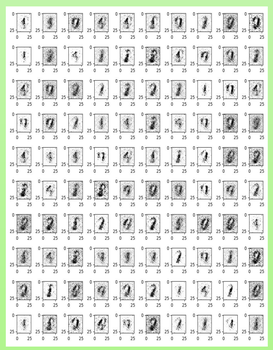


## Results

We have produced a GAN capable of replicating images from the MNIST dataset, which is comprised of hand-drawn numbers ranging from 0 to 9. These results are shown below for varying epoch quantities.

Reconstruction after first epoch



Reconstruction after 20th epoch

Reconstruction after 40th epoch