

Medical datasets often are extremely small due to the rarity of certain conditions, difficulty in obtaining standardized images, and expertise required to accurately label images. Therefore, for our project, we will first utilize a convolutional architecture (and perhaps other features) to classify and/or segment ROI in breast cancer images. We will further explore different methods to try to achieve the same success when constrained with a small subset of our original dataset. Our hope is to generalize the methods we explore here to other medical problems, where lack of data is an issue.

There are various papers regarding classification on mammograms, such as “Computational mammography using deep neural networks” by Dubrovina et. al., “Deep Learning in Mammography, Diagnostic Accuracy of a Multipurpose Image Analysis Software in the Detection of Breast Cancer” by Becker et. al., and “High-Resolution Breast Cancer Screening with Multi-View Deep Convolutional Neural Networks” by Geras et. al. We will also read the paper introducing the dataset we are using. We will use the CBIS-DDSM (Curated Breast Imaging Subset of the Digital Database for Screening Mammography).

There are several CNN advances we’ll employ, such as dense connections (between every pair of layers) and inception modules with multi-scale filters, including perhaps dilated convolutions. If we pursue a framing of the problem as segmentation rather than classification, we’ll explore hierarchical supervision (predict from an intermediate layer, projecting up to the resolution of segmentation labels if necessary with bilinear interpolation) of the network to further improve performance. If this is successful, we’ll experiment with some tried methods, as well as brainstorm some novel ways, to learn a good model from small datasets. Traditional methods of transfer learning such as reusing highly trained layers from other computer vision models are examples of the former.

In order to evaluate our results, we will use a variety of metrics: multiclass accuracy in a confusion matrix, false negative/positive rate for abnormalities vs. regular images. The false negative rate will be especially important to monitor; it tends to be much more important in evaluating medical diagnoses, since the consequences of a false positive diagnoses are much less severe than the consequences of a false negative diagnosis, especially for aggressive tumors.