MSBD6000B Project 3, Option 2:

Patch-based Convolutional Neural Network for Cancer Images Classification

**ABSTRACT**

In this report, we develop deep networking based on Convolutional Neural Network (CNN). Compared to traditional CNN directly for image-based label prediction, our method is to use a 2-level model, which utilizes CNN combined with Expectation-Maximization (EM) for patch-based label prediction, and then develop the second-level model to predict image-based labels using patch-based labels as input.

# INTRODUCTION

## Project Background

Breast cancer is the most common cancer in women worldwide. X-ray images are commonly used to help detect the cancer. Typically, the medical images are of much higher resolution than normal images. In this project, the image resolution is around 3328 x 4084. Applying CNN directly to the original high-resolution image is undesirable for 2 reasons. First, the downsampling required by CNN will lose discriminative information, while those cellular and sub-cellular level details are critical for detection in practice. Second, the CNN might only learn from one of the multiple discriminative patterns in a single image, which is not efficient in using data.

## Objective

The objective is to implement a model to detect if an X-ray image contains cancer tissue.

# DESIGN AND IMPLEMENTATION

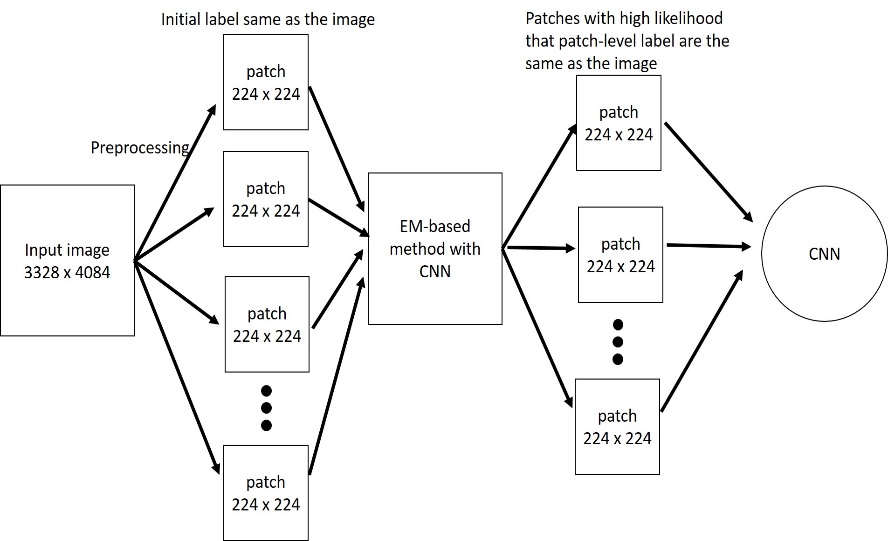
## Overview of solution

The key idea [1] is to select representative parts of the image, and learn their patterns and train a classifier to predict image label based on sub-image level patterns.

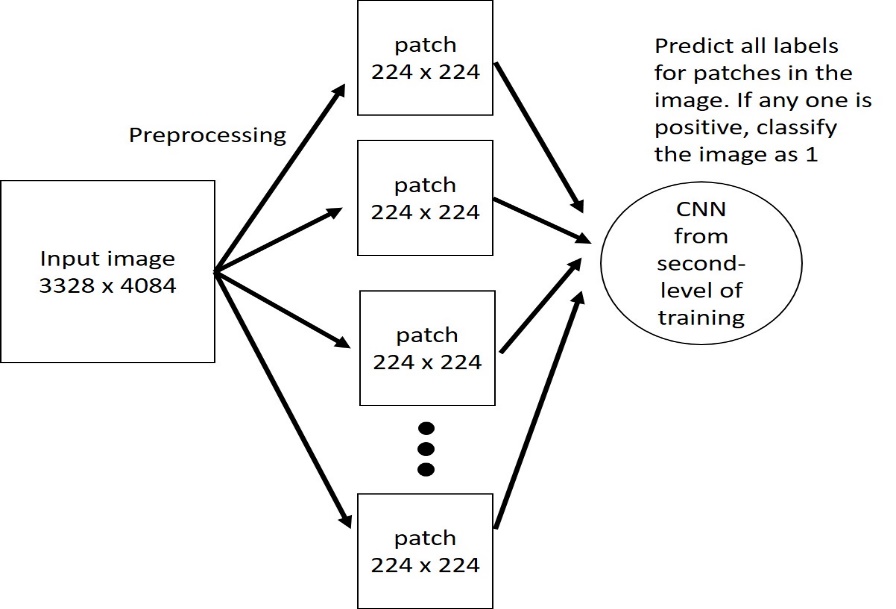
Before training, we preprocess the images by dividing them into smaller patches and remove patches are all dark. Then we initialize the labels of all patches as the same as the image. By applying Expectation-Maximization (EM) to the patches, only discriminative patches with high likelihood given the image distribution can be stayed as input for second-level CNN. The second-level CNN will be trained to learn the patterns of these discriminative patches.

In the testing stage, an input image will be passed to the same preprocessing and the generated patches are input for level-2 CNN. After that, all patches are with predicted labels. Finally, if any patch from the same image is positive, then the image will have label 1.

The overviews for training and testing are shown in figure 1 and 2.



(Figure 1. Overview of the training flow)



(Figure 2. Overview of the testing flow)

## Description of implementation

Maybe add some images in this session

Main Steps:

### Preprocessing:

Function: imagePreprocessing

cutDark: Cut the dark border for each image

splitImage: Split the image into small image with size 224 x 224

initEMPercentage: Assign initial label to patches

suffleFile: don’t know what it does

### EM with CNN:

Function: EMLoop

E step: EMTrain: train a CNN (pretrained model: MobileNet) to estimate the likelihood on whether a patch is discriminative given the image as a distribution

M step: drop the patch with the least likelihood

### Level-2 CNN:

Function: TrainModel

Train a model based on pretrained MobileNet to learn patterns of the discriminative patches.

### Prediction:

Function: TestModel

Pass the image through preprocessing and level-2 CNN. Give output image label 1 if any patch-level label 1 is found, otherwise output image label 0.

# EVALUATION

## Performance metrics

Validation accuracy, confusion matix…

## Experimental result

Add something if necessary

# REFERENCES

1. L. Hou, D. Samaras, T. M. Kurc, Y. Gao, J. E. Davis and J. H. Saltz, "Patch-Based Convolutional Neural Network for Whole Slide Tissue Image Classification," *2016 IEEE* Conferenceon Computer Vision and PatternRecognition(CVPR), Las Vegas, NV, 2016, pp.2424-2433. doi:10.1109/CVPR.2016.266 URL: <http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7780635&isnumber=7780329>