

# Deep Learning in Automated Breast Cancer Diagnosis from Microscopy Images

<sup>1</sup>Qiangqiang Gu, <sup>2</sup>Naresh Prodduturi, <sup>1</sup>Steven N Hart

<sup>1</sup>Department of Laboratory Medicine and Pathology, Mayo Clinic, Rochester, MN, <sup>2</sup>Department of Quantitative Health Sciences, Mayo Clinic, Rochester, MN

## ABSTRACT

Despite the numerous image classification approaches, previous research classifying normal versus tumor breast histology using the breast histology microscopy images has only focused on designing new deep learning models rather than tuning the combinations of the data preprocessing techniques, model parameters, and hyper-parameter configurations. We proposed a study to compare the performances of models with different combinations of hyper-parameters and data pre-processing techniques.

## CLINICAL PROBLEM

Breast cancer is one of the most common cancers in women. With early diagnosis, some breast cancers are highly curable. However, the concordance rate of breast cancer diagnosis from histology slides by pathologists is unacceptably low.

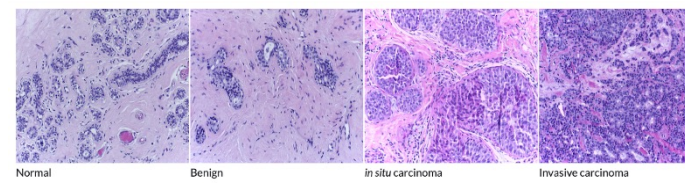
## IMAGE CLASSIFICATION

Classifying normal versus tumor breast tissues from breast histology microscopy images is an ideal case to use for deep learning and could help to more reproducibly diagnose breast cancer.

## AVAILABLE ALGORITHMS

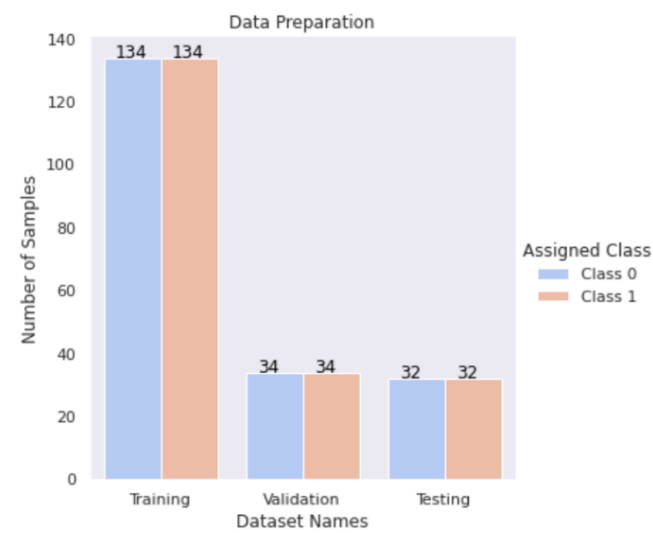
Model Index	Model Names	Deep Learning Approaches	Number of Sub-Neural Networks	Names of Sub-Neural Networks
I-1	InceptionV3	Transfer Learning	1	InceptionV3
D-1 to D-12	DenseNet201	Transfer Learning	1	DenseNet201
R-1	ResNet152	Transfer Learning	1	ResNet152
V-1	VGG19	Transfer Learning	1	VGG19
O-1	One-shot Learning	One-shot Learning	1	One-shot Learning
C-1 to C-26	Clustering-Constrained Attention Multiple Instance Learning (CLAM)	Transfer Learning, Attention Mechanism, Multiple Instance Learning	3	ResNet50, Attention Network, Instance Classifier, Slide Classifier

## BREAST CANCER HISTOLOGY DATASET - BACH

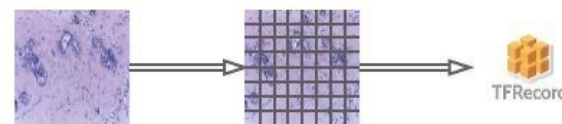


CLASS 0 (100 X 2 = 200) CLASS 1 (100 X 2 = 200)

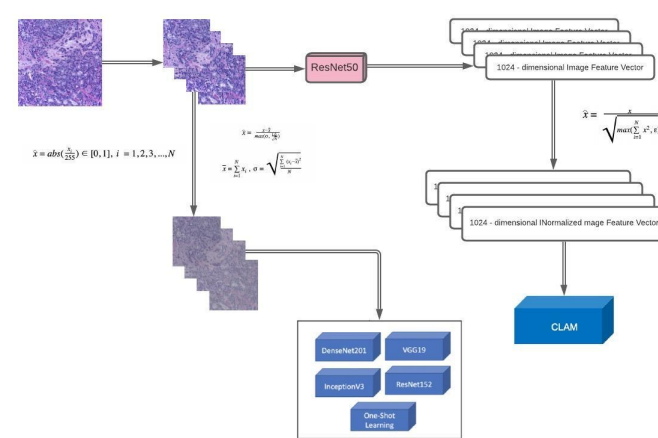
400 IMAGES



## DATA PREPARATION

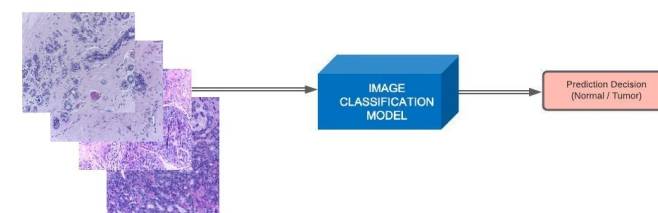


## IMAGE DATA PREPROCESSING



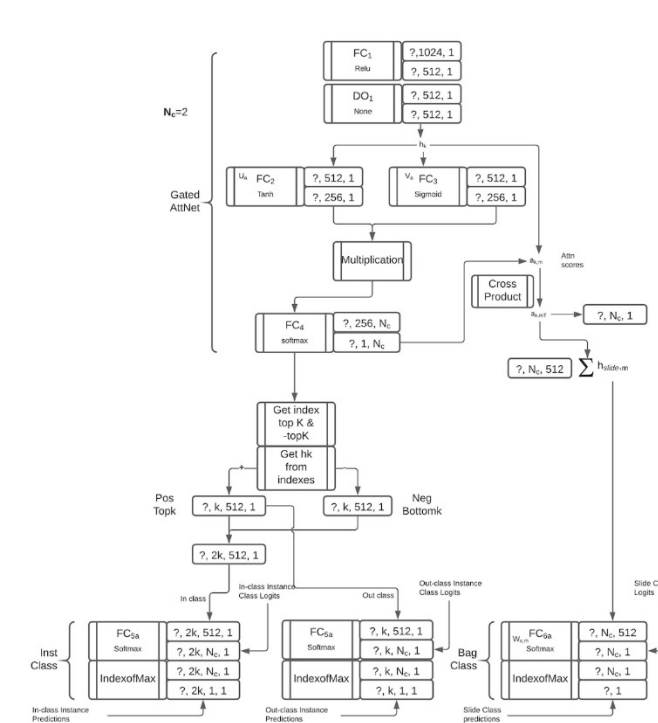
## METHODS

This approach includes two steps. We first tested the patch-level validation accuracy of tumor versus normal classification for 16 combinations of non-specialized deep learning models, image data pre-processing techniques, and hyper-parameter configurations, and chose the model with the highest patch-level validation accuracy. Then we computed the slide-level validation accuracy of the selected models and compared them with 26 hyper-parameter sets of a pathology-specific attention based multiple instance learning model.



Hyperparameters	Hyperparameters
Dropout Rate	Loss Function
Learning Rate	Training Layer
L2 Regularization	Image Standardization
Epochs	Image Scaling
Optimizer	L2 Normalization

## CLAM REIMPLEMENTATION



## CLAM COMPARISON RESULTS

- CLAM is original designed and implemented in PyTorch by Lu et al., which does not support ".tif" format images in BACH dataset
- We re-implemented in TensorFlow and compared with original CLAM on the same 40 TCGA breast histology whole slide images split into 10 cross-validation sets

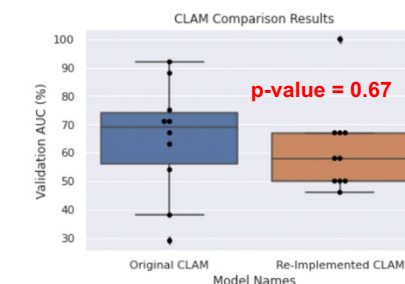
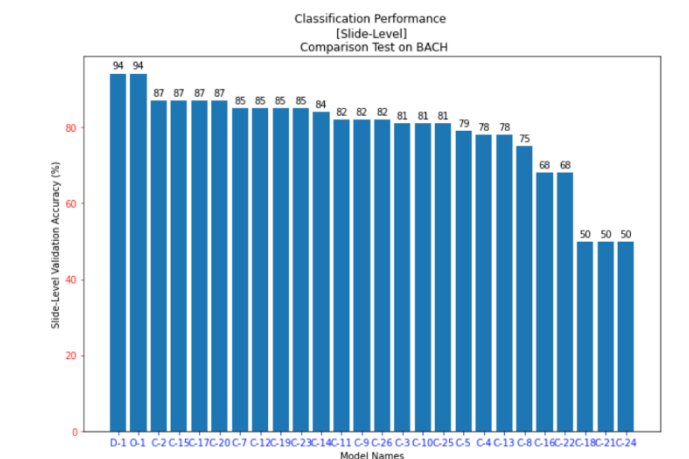
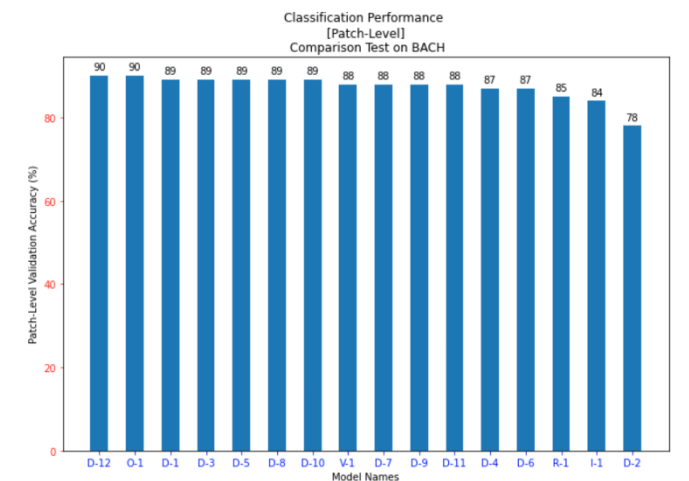


Figure 1. CLAM comparison test results of classification AUC scores on the validation WSIs from each of the 10 cross-validation sets.

## RESULTS



## CONCLUSIONS

The combination of image data preprocessing and hyper-parameter configurations have a direct impact on the performance of deep neural networks for image classification. To identify a well-performing deep neural network to classify tumor versus normal breast histology, researchers should not only focus on developing new models specifically for digital pathology, since hyper-parameter tuning for existing deep neural networks in the computer vision field could also achieve a high prediction accuracy.