

Using Convolutional Neural Networks (CNN) to Detect Invasive Ductal Carcinoma (IDC)



Nathan Acosta, Seyed Hosseini Darabi, Mohammad Mahmoudzadeh, Shaz Maknojia

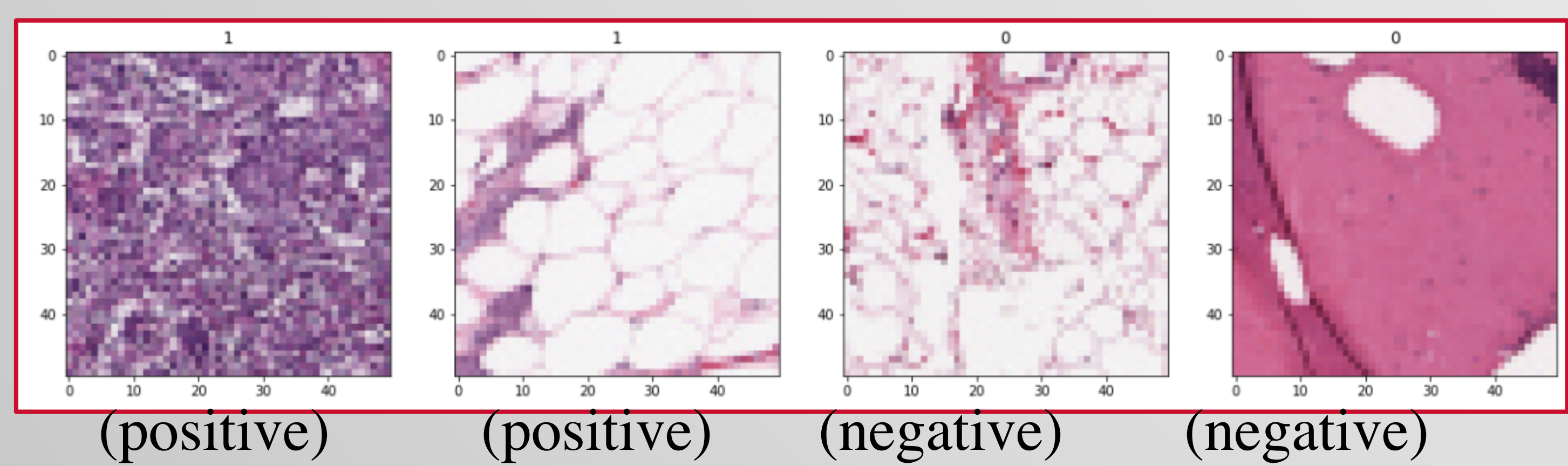
Department of Computer Science, University of Houston

Abstract

This study proposes a **convolutional neural network (CNN)** approach to **invasive ductal carcinoma (IDC)** detection and compares the effectiveness of various CNN architectures against different non-CNN machine learning algorithms. All the described architectures were guided using a large, public dataset of roughly 277,000, 50 x 50 pixel images. Validation tests are carried out for all quantitative results in accordance with the respective performance measures for each method. We find this proposed system to be successful, with an average CNN accuracy of **81%** and potential to reduce human error in IDC diagnoses. Moreover, our proposed CNN approach also outperforms the non-CNN machine learning algorithms' average accuracy of **72%**. We therefore find that **our proposed CNN approach to IDC detection improves accuracy by 9 percentage points when compared to other machine learning approaches.**

Background

Breast cancer is among the most prevalent forms of cancer for women in the United States. The most common type of breast cancer is **invasive ductal carcinoma (IDC)**, which comprises **approximately 80% of all female breast cancer diagnoses**. Consequently, the accurate identification and diagnosis of IDC is of extreme importance within the oncological field, and any approaches that can provide viable, high-quality classification are crucial insofar as they can **save time, reduce clinical error, and improve upon existing diagnostic infrastructure.**



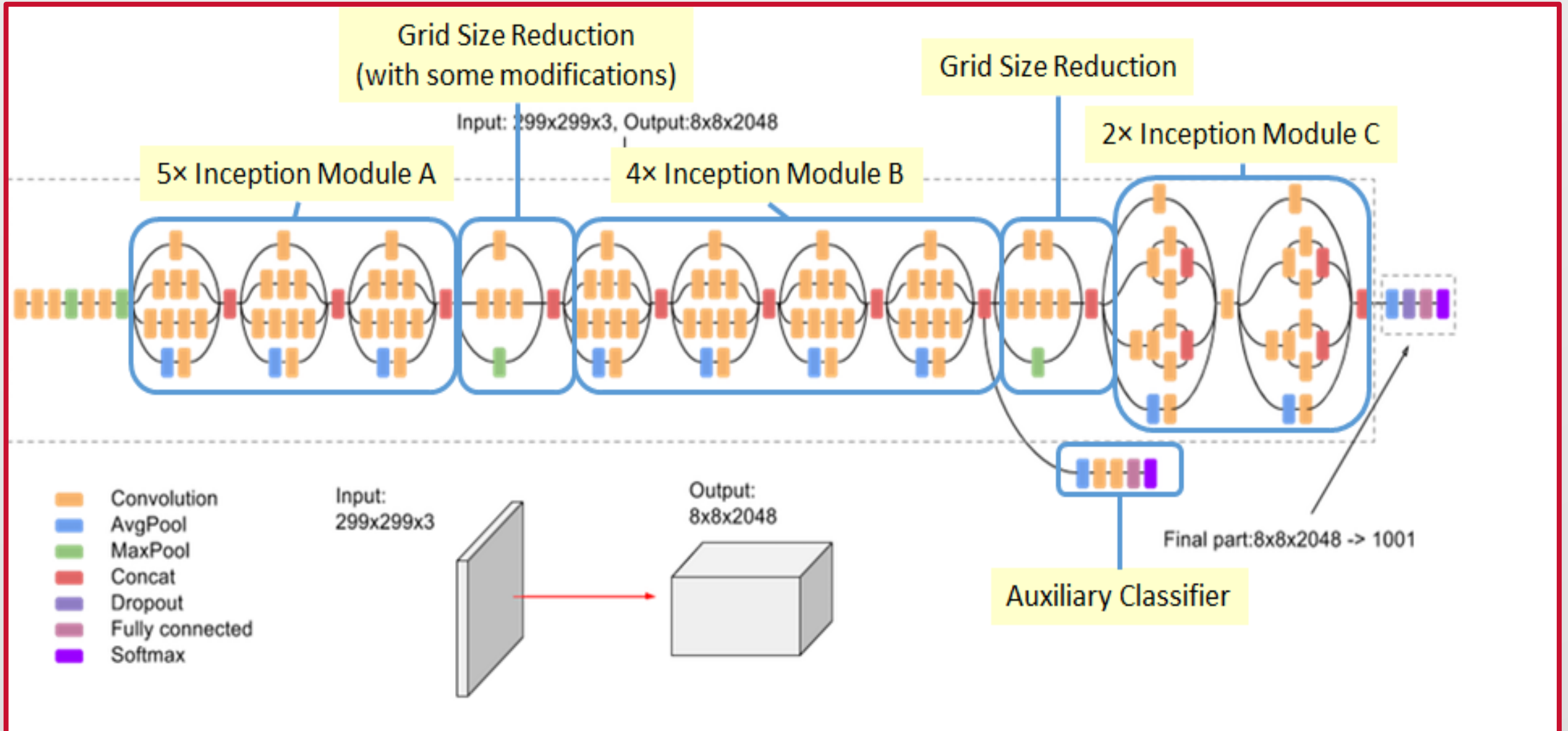
All images drawn from our dataset

Methods

We implement **8 distinct models** and conduct an evaluation of their results. All images underwent preprocessing techniques such as **resolution scaling** and **color channel scaling** before being trained on. The more complex CNN models—ResNet, Inception, and EfficientNet—were imported as **keras pretrained models** to reduce computational costs. All other models were trained solely on the histopathology images. Test accuracy was determined via a **validation set approach**.

model_C.summary()		
Model: "sequential_2"		
Layer (type)	Output Shape	Param #
=====		
conv2d_8 (Conv2D)	(None, 48, 48, 16)	448
max_pooling2d_3 (MaxPooling 2D)	(None, 24, 24, 16)	0
conv2d_9 (Conv2D)	(None, 22, 22, 32)	4640
max_pooling2d_4 (MaxPooling 2D)	(None, 11, 11, 32)	0
conv2d_10 (Conv2D)	(None, 9, 9, 16)	4624
max_pooling2d_5 (MaxPooling 2D)	(None, 4, 4, 16)	0
flatten_2 (Flatten)	(None, 256)	0
dense_5 (Dense)	(None, 50)	12850
dense_6 (Dense)	(None, 1)	51
=====		
Total params: 22,613		
Trainable params: 22,613		
Non-trainable params: 0		

5-Layer Simple CNN



InceptionV3 Architecture

Results

Model	Accuracy ↓	Brief Description
Simple Sequential CNN	86.96%	9-Layer Convolutional Neural Network (Implemented using tensorflow.keras)
Inception_V3 Pretrained	83.37%	42-Layer Convolutional Neural Network Pretrained on Imagenet dataset
ResNet_50V2 Pretrained	80.04%	50-Layer Residual Neural Network Pretrained on Imagenet dataset
Random Forest	76.21%	Non-Parametric Ensemble Learning Classifier
SVM	76.15%	Deep Learning Supervised Learning Classifier
EfficientNet Pretrained	72.70%	237-Layer Convolutional Neural Network Pretrained on Imagenet dataset
Decision Tree	72.30%	Non-Parametric Supervised Learning Classifier
KNN	62.40%	Non-Parametric Supervised Learning Classifier

Conclusion

Our **Simple Sequential CNN** model performed best, with the highest accuracy and lowest CPU cost relative to the other CNN models. We believe the **higher test accuracy** is linked directly to the **training methods**; the 5-layer CNN model was **trained from scratch**, whereas the pretrained models had fixed convolutional training parameters.

Future Direction

In the future, we would use **better hardware**—thereby enabling us to train **more sophisticated models** from scratch. We would likewise implement **more sophisticated preprocessing methods** and **utilize higher quality images** to allow for more efficient classification.

Acknowledgments

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