



Politechnika Wrocławskiego

Breast Cancer Histopathological Image Classification using Convolutional Neural Network

Contents

- 1) Motivation
- 2) Project Goals
- 3) Related Works
- 4) Dataset
- 5) Research Environment
 - a) PyTorch
 - b) Microsoft Azure
- 6) Proposed Methodology
 - a) CNN
 - b) Transfer Learning
 - c) AlexNet
- 7) Experiments
- 8) References

Motivation

“

Thousands of people around the globe die every year as result of Breast Cancer. Early detection of breast cancer can save millions of lives each year. Detection of cancer tissues is possible through several ways like MRI scan, Mammogram, breast Ultrasound and Histopathology images.



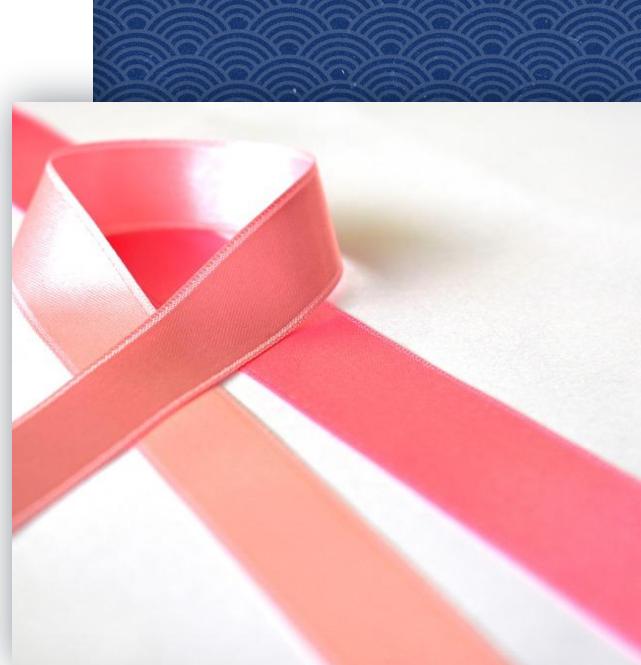
3/28

Figure1:Breast cancer pink ribbon

Project Goal

“

Our project is about developing automated system which can detect cancer from the histopathology images.



4/28

Figure2: Breast cancer pink ribbon

Related Works

Fabio Spanhol
(2016) Breast
cancer
histopathology
image
classification
using cnn

BreakHis dataset: contains 9000 images of malignant/benign cells at different magnification factors

Disadvantage: High resolution images

Solution: Reduce the size of images and extract random patches of 32x32px from them

- ◎ Several deep neural networks architectures were tested among them were LeNet, and AlexNet
- ◎ AlexNet displayed the best performance
- ◎ To achieve the best results, the following layers were used: Input layer, 3 Convolutional layers, Pooling layers, 3 ReLu Layers , Fully connected layers. 70% training , 30% test data.

Results

- Training time: 3 hours for random patch strategy
- Accuracy: Min - 79% , Max 89.6%
- Training on 64 x 64 px patches , gave the best results

Related Works

Yassir Benhammou
Siham Tabik
Boujemâa Achchab
Francisco Herrera

A first study exploring the performance of the state-of-the art CNN model in the problem of breast cancer

- ◎ **Dataset:** Spanhol et al. introduced BreakHis dataset , composed of 7909 microscopic biopsy images of breast tumors tissue, using different microscope magnifying factors.The dataset is divided into two main classes, malignant and benign .
- ◎ Use the state-of-the art CNN architecture, Inception v3 and analyze its capability to achieve better results than those obtained by their related works on the same dataset.
- ◎ Use DeCaf Features approach to transfer knowledge learnt by an available Inception v3 model pre-trained on ImageNet dataset, in order to solve the specific task of breast cancer classification.
- ◎ They compared their works with their related works and got the result that the model used CNN+TL is the best for F1 score image level.The accuracies are 93.0% 88.9% 89.4% 86.9% for X40 X100 X200 X400 scope.

Dataset

- ◎ 356,310 images in total
- ◎ 198,738 benign and 157,572 malignant tissues
- ◎ All images are 50x50px RGB patches extracted from mount slide images of breast cancer
- ◎ Organized in classes: class 0 = benign, class 1 = malignant
- ◎ Example data set images:

Class 0:



Class 1:

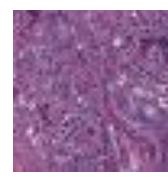
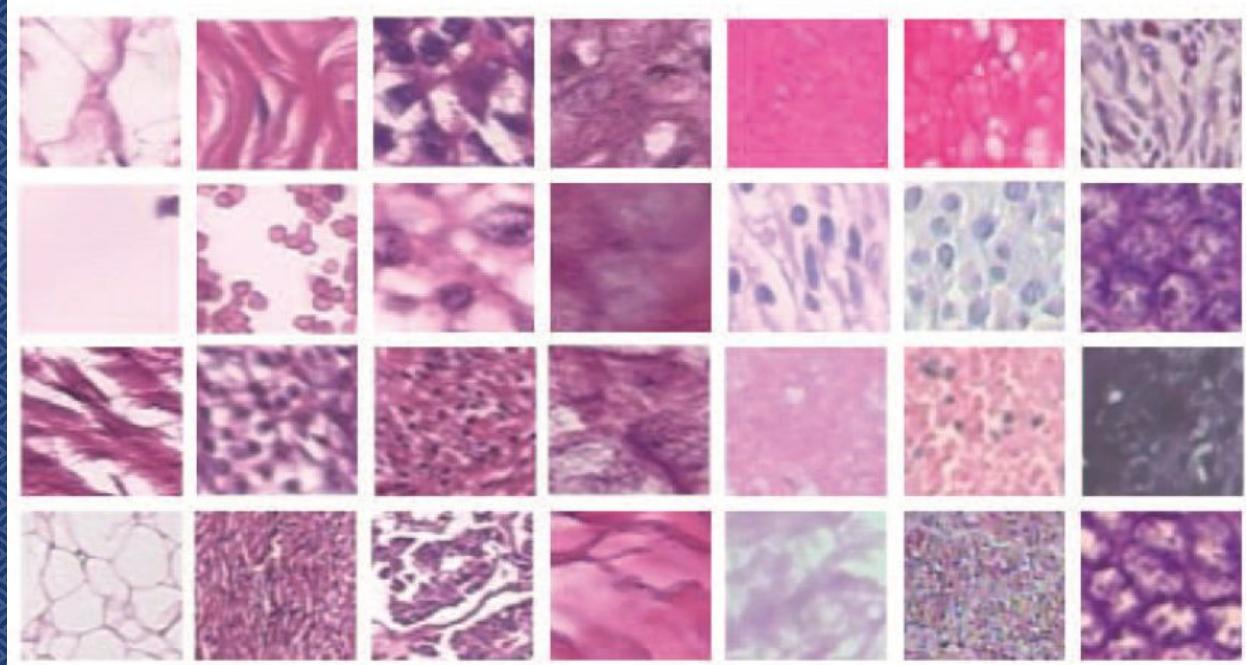


Figure 5:Benign

Figure 6:Malignant



9/28

Figure7: <https://www.kaggle.com/paultimothymooney/breast-histopathology-images>

Dataset Preprocessing

Randomizing images for training by horizontal flip and random rotation and cropping them to get rid of empty pixels and resizing for AlexNet input size requirements. At the end transforming all images to tensors to feed into network.

```
dataset_transform = transforms.Compose([
    transforms.Resize(254),
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(0, 270),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
])
```

10/28

Research Environment

Implementation Language: Python

Environment: Microsoft Azure VM

Libraries: PyTorch

PyTorch

- ◎ Open source - large community of developers have created many useful tools and libraries around PyTorch
- ◎ Easy to learn, easy to use.
- ◎ Well documented
- ◎ Dynamic approach to graph computation

Microsoft Azure

Why?

Training neural network on our devices was impractical. Average training time for one epoch on Macbook pro was 4 hours.

Results

Setting up Azure VM allowed us to train our model on hardware that is actually suitable for training deep neural networks. **N-Series GPU** enabled VM's were used for high speed computation. Average training time for one epoch was 5 minutes. This is a huge difference !

CNN(Convolutional Neural Network)

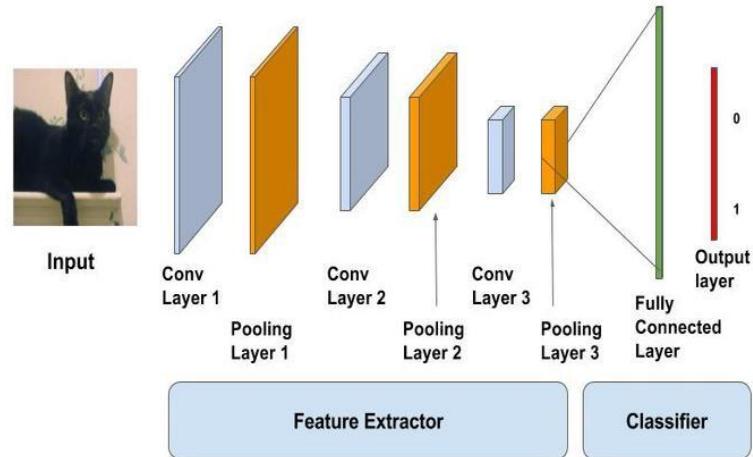


Figure 8 :Progress of CNN

Convolutional Layer

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0



5 x 5 – Image Matrix

1	0	1
0	1	0
1	0	1

3 x 3 – Filter Matrix



1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved Feature

Figure 9 : Image matrix multiplies kernel or filter matrix

RELU

The purpose of applying the rectifier function is to increase the non-linearity in our images.

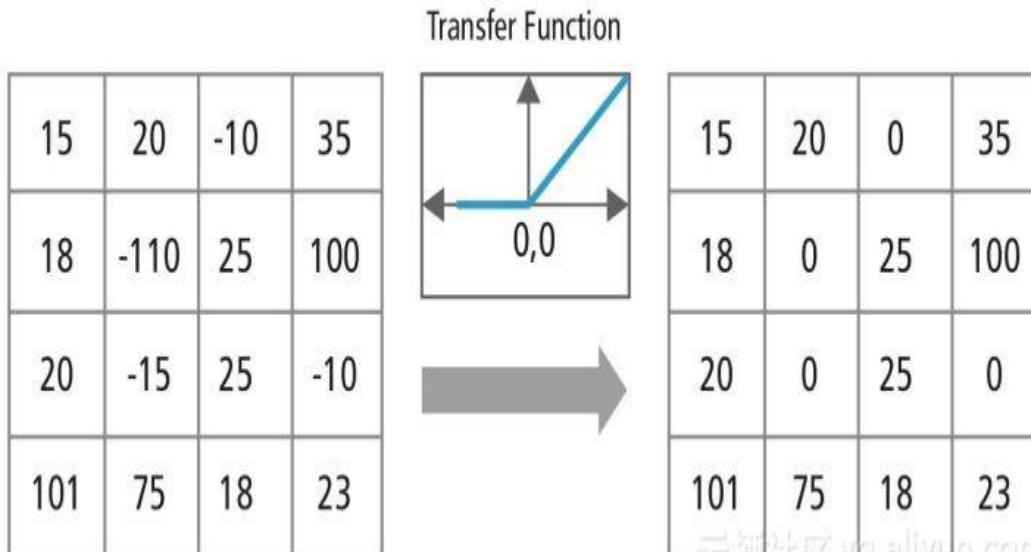
$$F(x) = \max(0, x)$$


Figure 10 : ReLU operation

Pooling Layer

Pooling layers section would reduce the number of parameters when the images are too large.

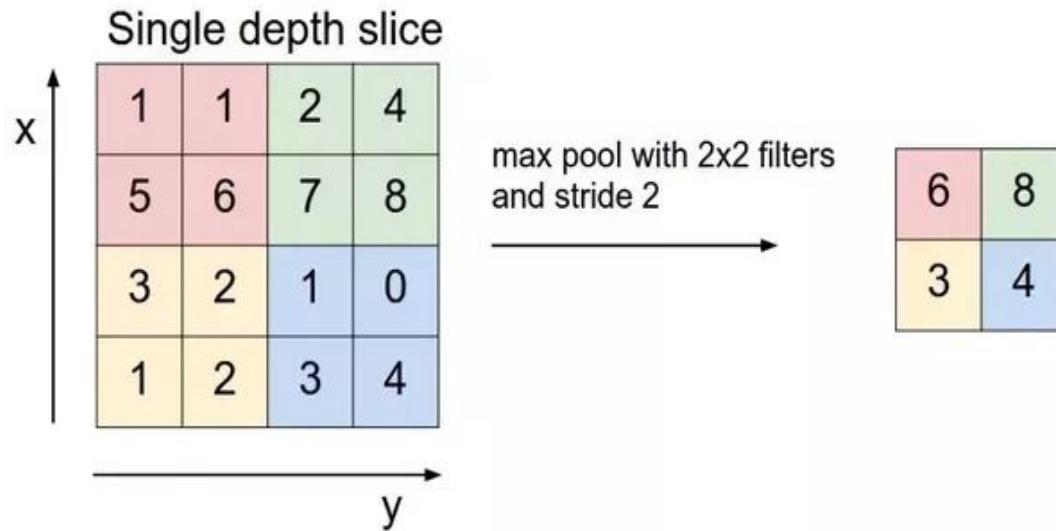
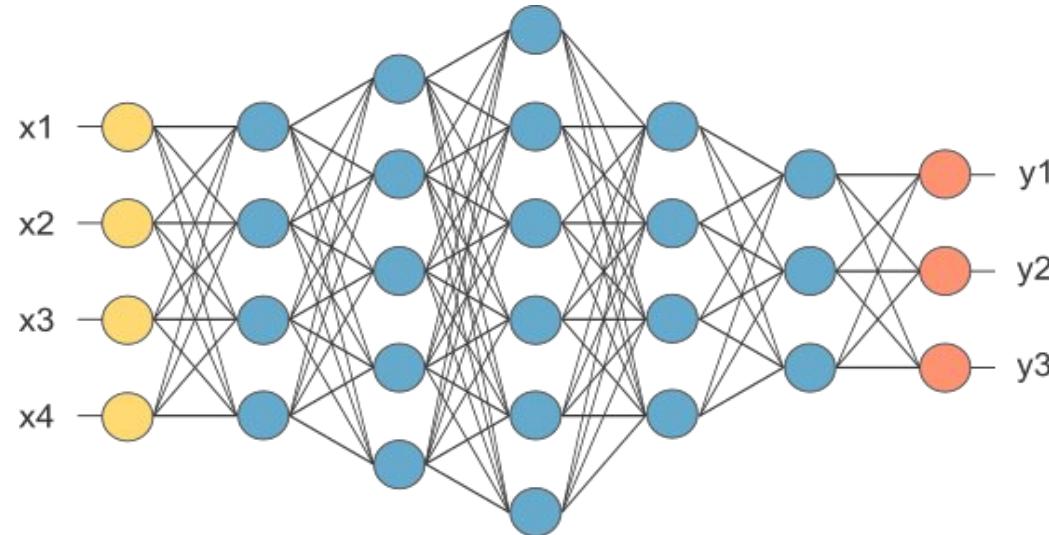


Figure 11: Max Pooling

Fully Connected Layer

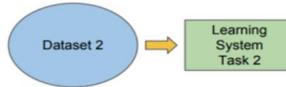
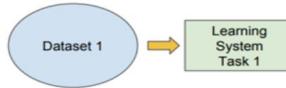
Figure 12:
After
pooling
layer,
flattened
as FC
layer



Transfer Learning

Traditional ML

- Isolated, single task learning:
 - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks



vs

Transfer Learning

- Learning of a new tasks relies on the previous learned tasks:
 - Learning process can be faster, more accurate and/or need less training data

Traditional Learning vs Transfer Learning

Figure 13 :Traditional Learning vs Transfer Learning

AlexNet

- ◎ It has 60 million parameters and 650,000 neurons
- ◎ AlexNet consists of 5 Convolutional Layers and 3 Fully Connected Layers
- ◎ The first two Convolutional layers are followed by the Overlapping Max Pooling layers that we describe next. The third, fourth and fifth convolutional layers are connected directly. The fifth convolutional layer is followed by an Overlapping Max Pooling layer, the output of which goes into a series of two fully connected layers. The second fully connected layer feeds into a softmax classifier with 1000 class labels.

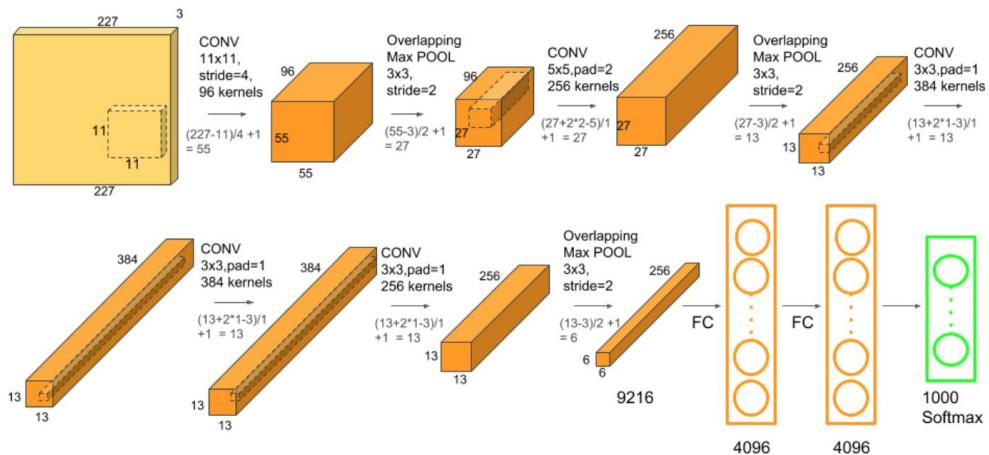


Figure 14:: AlexNet Architecture

Experiments

Experiment 1

Experiment 2

Experiment 3

For simplicity and due to time constraints all experiments were conducted on 15 epochs

15 epochs ~ 1 hour training

**Comparison of Adam,
SGD optimizers**

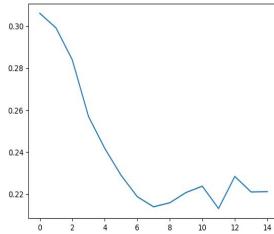
**No Dropout vs
Various Dropout
rates**

**Analysis of Learning
Rates to find the
most suitable one**

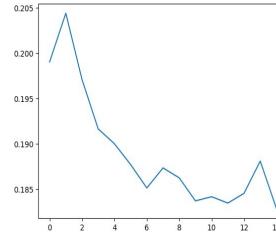
Experiment 1

Analysing performance of SGD vs Adam

SGD



ADAM



- Final train accuracy: 77%
correct: 185185 total: 237540
- Final test Accuracy :79%
correct: 94425 total: 118770
- Final train accuracy: 81%
correct: 192115 total: 237540
- Final test Accuracy :82%
correct: 97817 total: 118770

Experiment 2

Analysis of Learning Rate

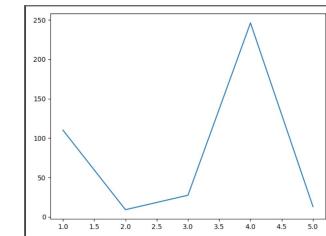
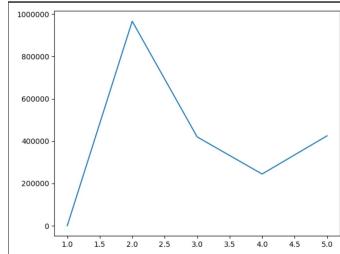


Fig. Shows loss explosion for 0.1 and 0.01 learning rates

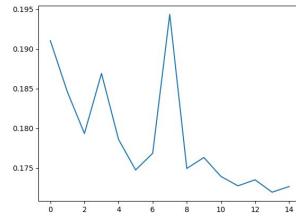
Learning Rate	Final Train Accuracy	Final Test Accuracy	The best loss
0.1	62%	73%	CAUSES LOSS EXPLOSION 223.3863570690155 Stopped at 5 epoch
0.01	65%	78%	9.18007541820407
0.001	79%	81%	0.1892446418642066
0.0001	81%	82%	0.1851455548312515
0.00001	82%	82%	0.1780376098467968 4

Experiment 3

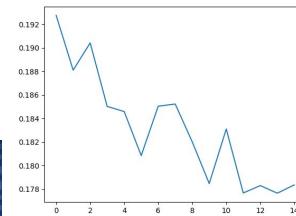
Analysis of Dropout Rate

Using No Dropout proved to be better than model with dropouts set to various rates

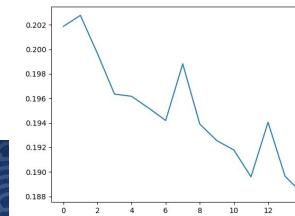
Dropout	Final Tran Accuracy	Final Test Accuracy	The best loss
No dropout	83%	83%	0.1719674781197682
0.2	81%	82%	0.1776675339206122
0.5	80%	81%	0.18826697597978637
0.8 Stopped early at 11th epoch	77%	79%	BEST TRAIN ERROR: 0.21071084344293922



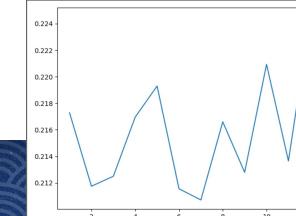
No dropout



0.2



0.5



0.8

OUR BEST RESULT

Model configuration:

Dropout: 0.2

Learning rate: 0.00001

Number of epochs: 80

Stopping condition set to 8 epochs

Optimizer: Adam

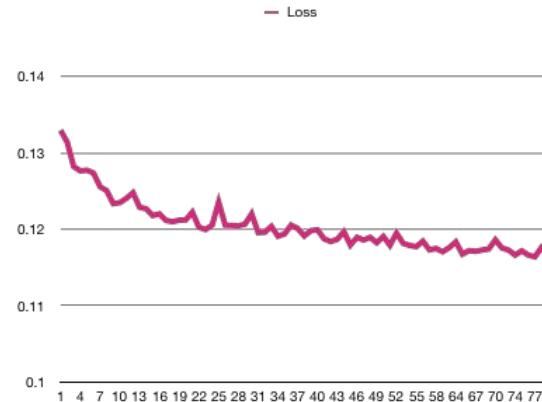
Train accuracy: 83%

Test accuracy: 85%

Best loss: 0.116553117812146

Training time: around 3 hours

Our hypothesis is that better accuracy is possible with the greater amount of epochs. The training stopped because it reached a max number of epochs but the loss was still decreasing.





Demo

26/28

References

- Fig 1, Fig 2 : <https://pixabay.com/>
3. *Spanhol, Fabio & Soares de Oliveira, Luiz & Petitjean, Caroline & Heutte, Laurent.* (2016). *Breast Cancer Histopathological Image Classification using Convolutional Neural Networks.* 10.1109/IJCNN.2016.7727519.
4. <https://www.kaggle.com/paultimothymooney/breast-histopathology-images>
5. [Figure13]:<https://www.learnopencv.com/understanding-alexnet/>
6. [Figure14]:
<https://www.learnopencv.com/understanding-alexnet/>
- 7.[Fig8]:<https://medium.com/@sdoshi579/convolutional-neural-network-learn-and-apply-3dac9acfe2b6>
- 8.[Fig9,10,11,12]:<https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148>