Breast Cancer Detection

Implementing Artificial Neural Networks with TensorFlow
University of Osnabrueck
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Alexandra Benova, Christina Gollub and Lisa Mesch

Overview

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Our motivation

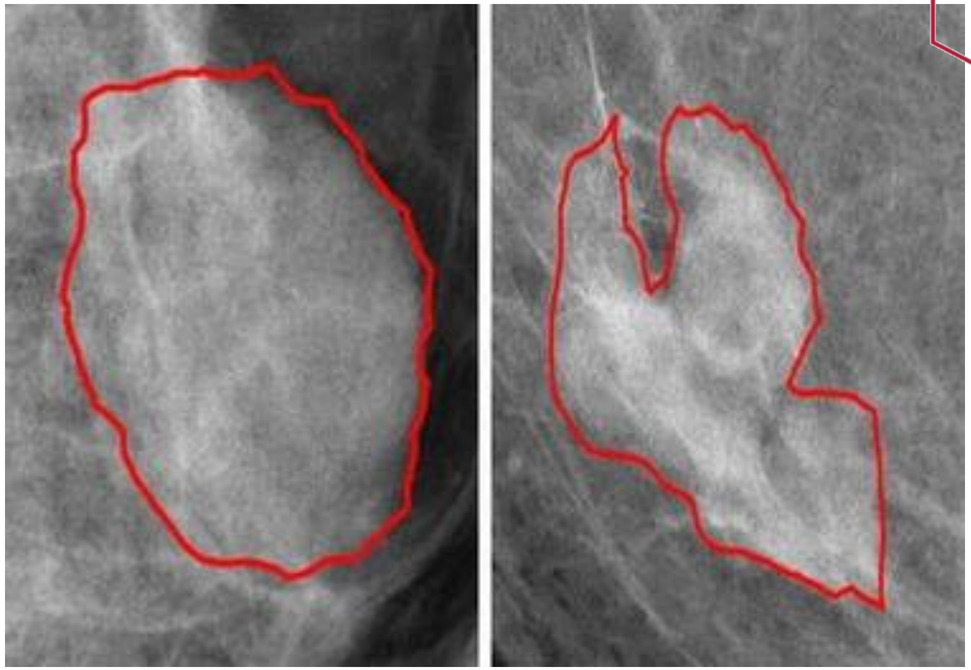
Breast Cancer is one of the most common oncological diseases among women world-wide and therefore, remains a significant health concern.

3	30	57
The 3rd most common cancer in Bulgaria	**Accounting for 30% of all cancer cases in Germany**	**57000 new cases each year in the UK**

As a team of three women, we have chosen to focus on breast cancer detection, as we believe it is a highly significant and compelling topic.

Our motivation

- mammography is the most effective tool for early detection
- highly skilled radiologists are needed to correctly analyze these screenings
- due to human error such as fatigue or distraction, false-positive mammography screening
  in Europe can range from 8 to 21 percent



https://biomedical-engineering-online.biomedcentral.com/articles/10.1186/s12938-017-0332-0/figures/1

benign mass with regular shape

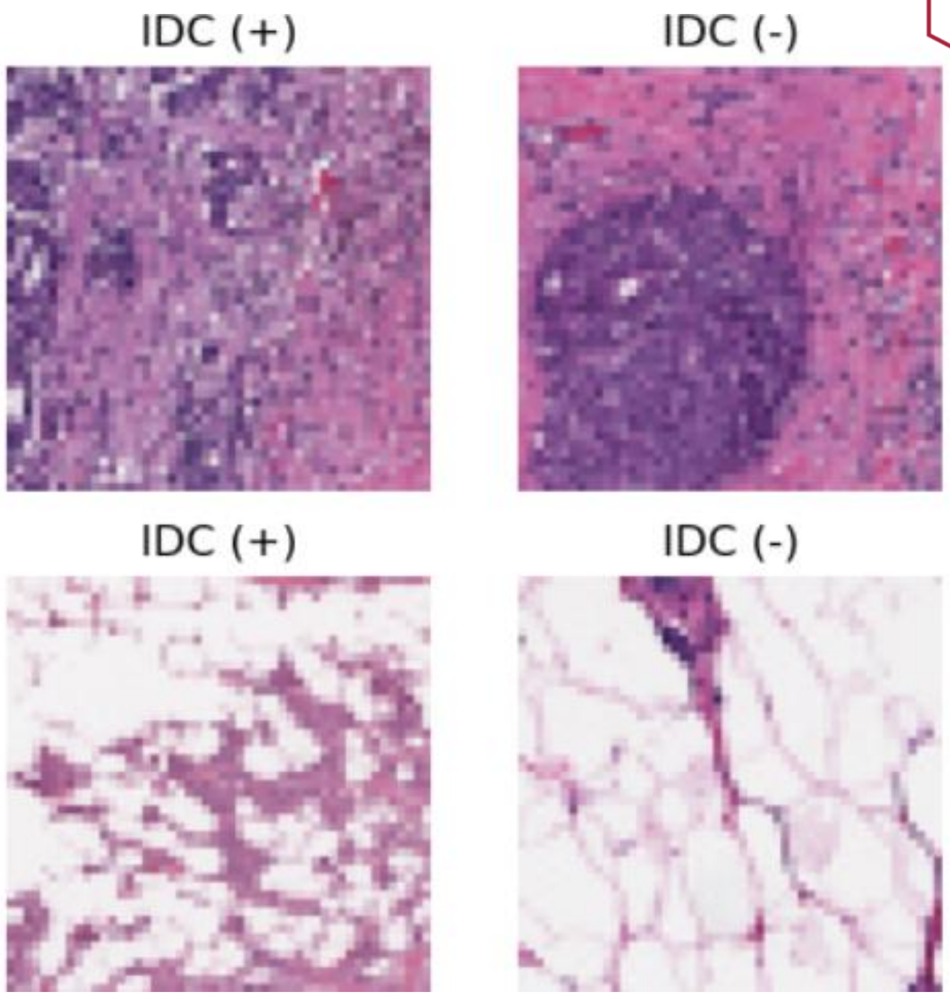
malignant mass with irregular shape

Our ultimate goal is to improve the chances of successful treatment and save lives. We will do this by exploring different architectures, like the ResNet50, VGG16 and InceptionV3, used with a transfer learning method. These models are compared with each other and a basic convolutional neural network.

The methods we used

Our dataset

- “Breast Histopathology Images” from Paul Mooney on Kaggle
- Histopathology Images of the most common sub-type of all breast cancers, **Invasive Ductal Carcinoma (IDC)**.
- 277,524 patches of size 50 x 50 from an original dataset of 162 whole mount slides
- 198,738 IDC negative and 78,886 IDC positive images



The methods we used

Our CNN model

- consists of several convolutional and pooling layers which are followed by a few dense layers
- convolutional layers are added to the model by Conv2D layers with a 32 filter of size (3,3) and a ReLU activation function
- dropout layer with a rate of 0.25 after each pooling layer
- Flatten layer to convert the output of the convolutional layers into a 1D vector
- dense layers that have 128 and two neurons respectively and ReLU and sigmoid activation functions

The methods we use

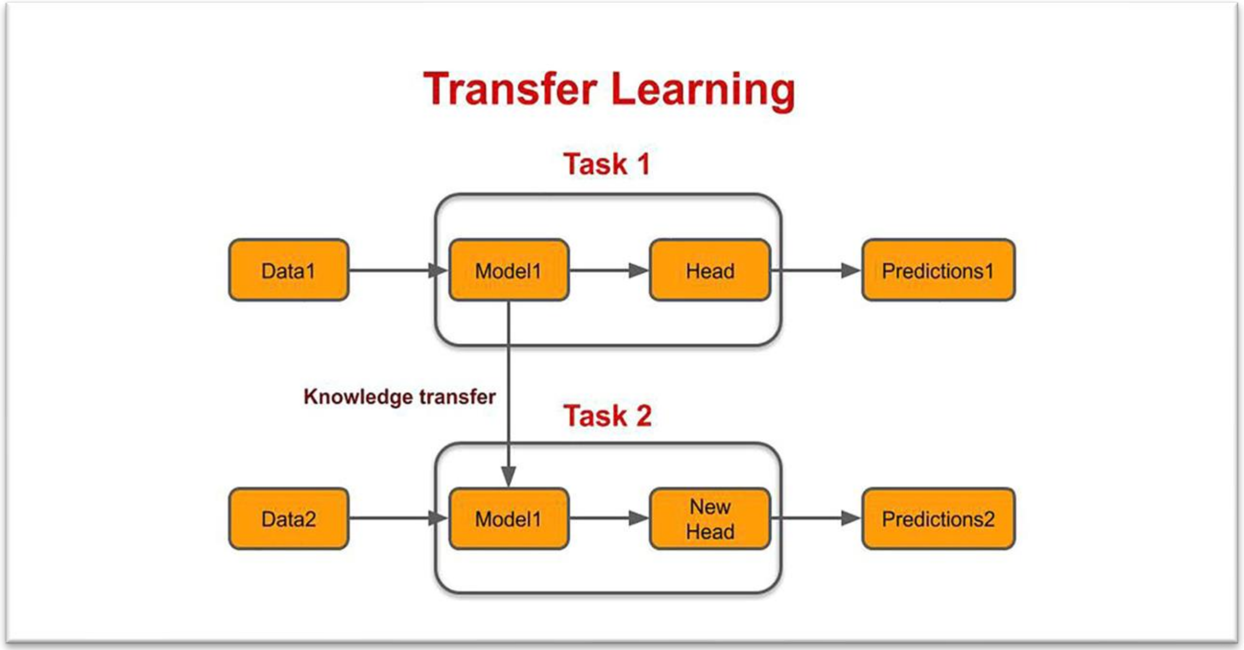
Transfer Learning (TL)

- transfer of learned features from a pre-trained model to a new network model
- such as weights and biases
- pre-trained models have already been trained on similar domains
- can save significant time and computational power
- quicker and more efficient training of new networks
- Architectures we used for TL:

  - VGG16

  - ResNet50

  - Inception V3

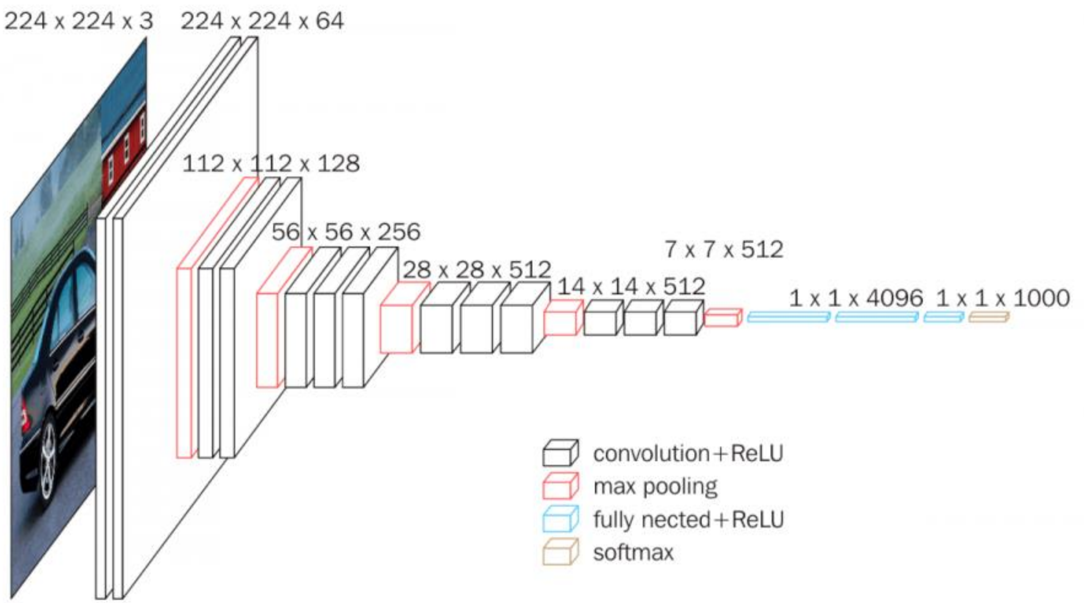


Bhavsar, P. (2019, December 5). An Ultimate Guide To Transfer Learning In NLP. [Transfer learning graph].

Architectures for TL

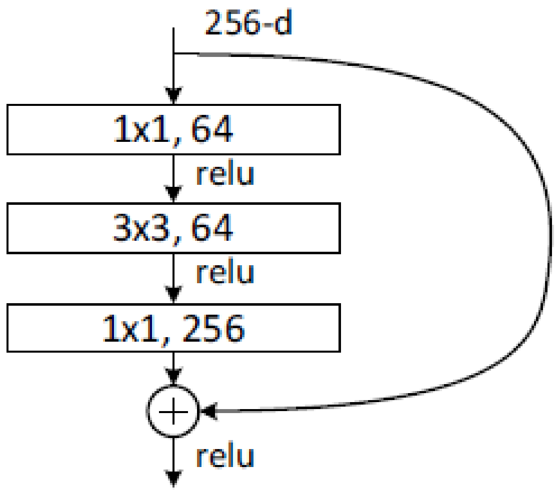
VGG16

- one of the best computer vision models available
- used for object detection and classification, with the ability to classify 1000 images of 1000 different categories with an accuracy of 92.7 %
- has 16 weight layers and 21 layers in total
- uses 3x3 filters with stride 1 and consistent padding, along with 2x2 max pool layers
- number of filters increases from 64 to 512 as you move through the layers



https://neurohive.io/en/popular-networks/vgg16/

Architectures for TL



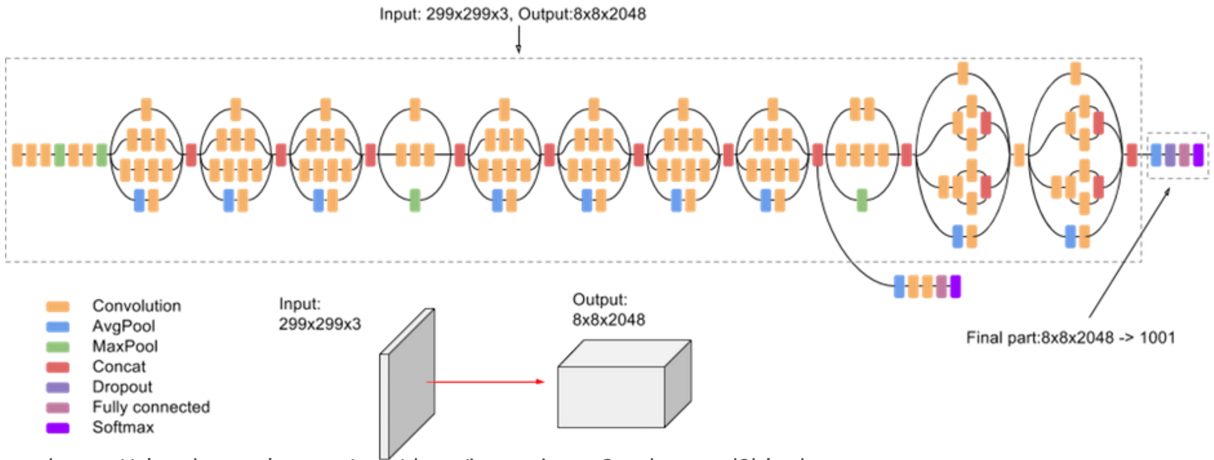
ResNet-50

- Designed by Microsoft to solve the problems of vanishing gradients and degradation
- ResNet18, -34, -50, 101 and 152 and we'll be using the ResNet-50
- a neural network with up to 152 layers was able to be trained while still having a lower complexity than VGGs
- ability to learn features at multiple levels of abstraction
- highly effective image classification tasks, including medical image analysis
- ResNet50 is a more complex and deeper residual neural network with 50 layers

Architectures for TL

Inception V3

- designed by google to address some of the previous model limitations, such as high computational requirements and overfitting
- combination of convolutional and pooling layers with various filter sizes and depths to extract features from images
- followed by global average pooling and a softmax output layer for classification
- because of improved accuracy and efficiency, it’s popular choice for image-related applications, including object detection, segmentation, and transfer learning



https://cloud.google.com/tpu/docs/inception-v3-advanced?hl=de

Results

CNN result:

True Positive **25641**	False Negative **987**
False Positive **1940**	True Negative **2946**

Accuracy: 90.7 %

F1 score: 94.60 %

VGG16 results with TL:

True Positive **25948**	False Negative **680**
False Positive **2730**	True Negative **2156**

Accuracy: 90.27 %

F1 score: 93.83 %

ResNet50 results with TL:

True Positive **25852**	False Negative **810**
False Positive **2295**	True Negative **2557**

Accuracy: 90.15 %

F1 score: 94.33 %

InceptionV3 results with TL:

True Positive **25641**	False Negative **987**
False Positive **1940**	True Negative **2946**

Accuracy: 84.53 %

Comparison

Jaamour

- Trained on the CBIS-DDSM (2,620 scans) and the mini-MIAS datasets (322 scans)
- MobileNetV2 (**ACC: 0.67, F1 score: 0.66**)
- VGG19 (**ACC: 0.65, F1 score: 0.51**)

Our results

- Trained on the "Breast Histopathology Images" (277,524 scans)
- VGG16 (**ACC: 0.902, F1 score: 0.94**)
- ResNet50 (**ACC: 0.901, F1 score: 0.94**)
- InceptionV3 (**ACC: 84.53**)

Falconi at al.

- Trained on the CBIS-DDSM dataset (2,620 scans)
- ResNet50-TL (**ACC: 0.86, F1 score: 0.86**)
- VGG16-TL (**ACC: 0.84, F1 score: 0.85**)

Limitations

- As we saw, our results achieved the highest accuracy across all models compared to those of Falconi and Jaamour

- However observed differences in accuracy may be attributed to various factors:
  - differences in the dataset size
  - pre-processing techniques, like the input image size
  - class balance between the training and test data or the split of begnin and malignant scans

These factors should be considered when interpreting the results.

Challenges we faced

- Trying to work out the best work split, especially under the condition that we were all at different places around Europe
- Struggle with finding the perfect data for this project and its implementation
- Facing difficulties with selecting and implementing certain architectures such as the ResNet50 and InceptionV3 for Transfer Learning
- It was a challenge to set up the hardware required to train large models that need significant computing power

Conclusion

- Breast cancer is a significant health concern and mammography testing is the most effective tool for early detection.
- We explored deep learning models including ResNet50, VGG16, and InceptionV3 with the transfer learning technique for breast cancer detection.
- Our experimentation allowed us to identify the most promising models.
- Our study was limited by dataset size and computational resources.
- We hope our work contributed to the development of more accurate and efficient deep learning models for breast cancer detection.

Questions & answers

write an email to:

abenova@uni-osnabrueck.de

cgollub@uni-osnabrueck.de

limesch@uni-osnabrueck.de

Thank you!

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