Detecting Breast Cancer In Histopathology Images

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Summary

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- Transfer Learning: VGG19
- Custom CNN
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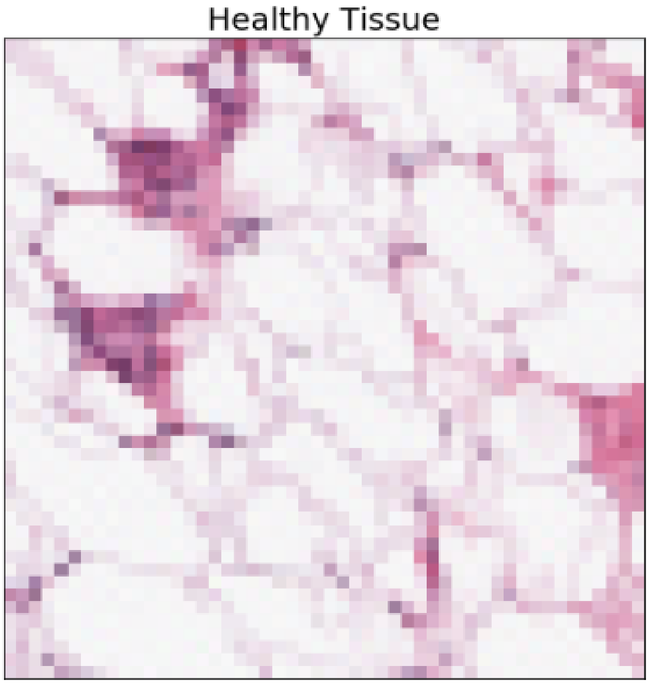
Motivation

- Invasive Ductal Carcinoma (IDC) is the most common subtype of breast cancer.
- Diagnosis and aggressiveness grade are determined by visually analyzing histopathology images.
- Visual analysis is a time consuming and demanding task prone to error.
- This work proposes a model to automatize the detection of IDC in histopathology images.

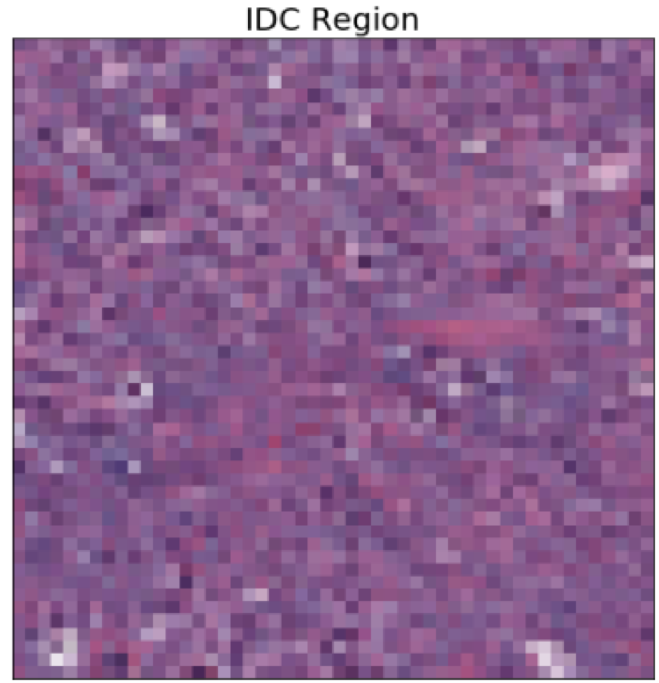
Data set

Image slides divided in 50x50 pixels color images.

Negative or 0 class



Positive or 1 class



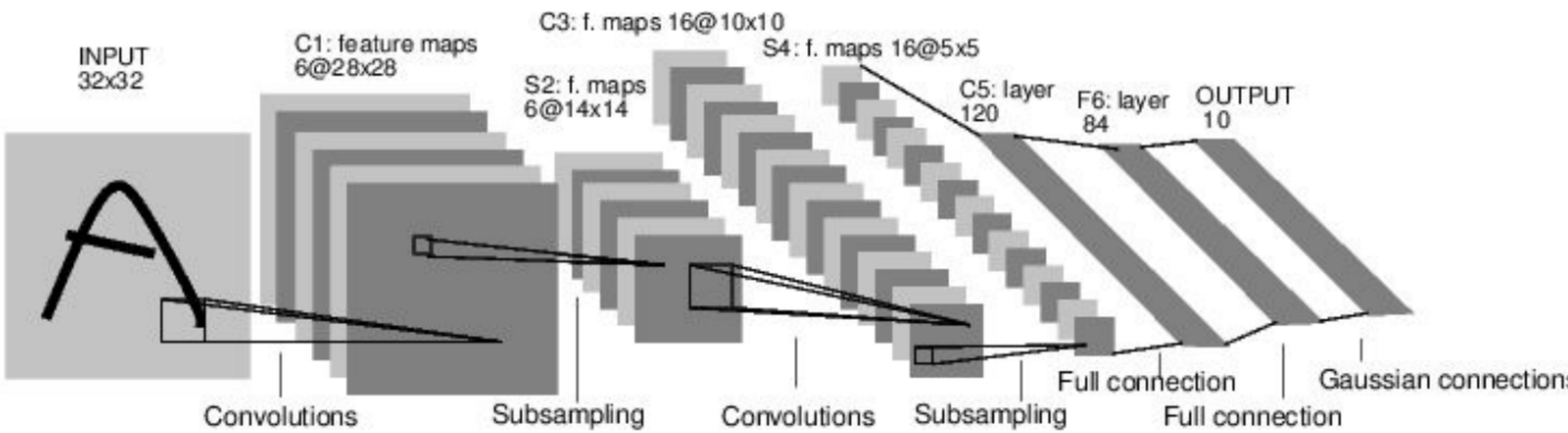
Imbalanced classes: 2.5 to 1 in favor of negative class.

Simple model:

All images classified as negative.

Accuracy: 71.38%

Convolutional Neural Networks (CNN or CovNet)

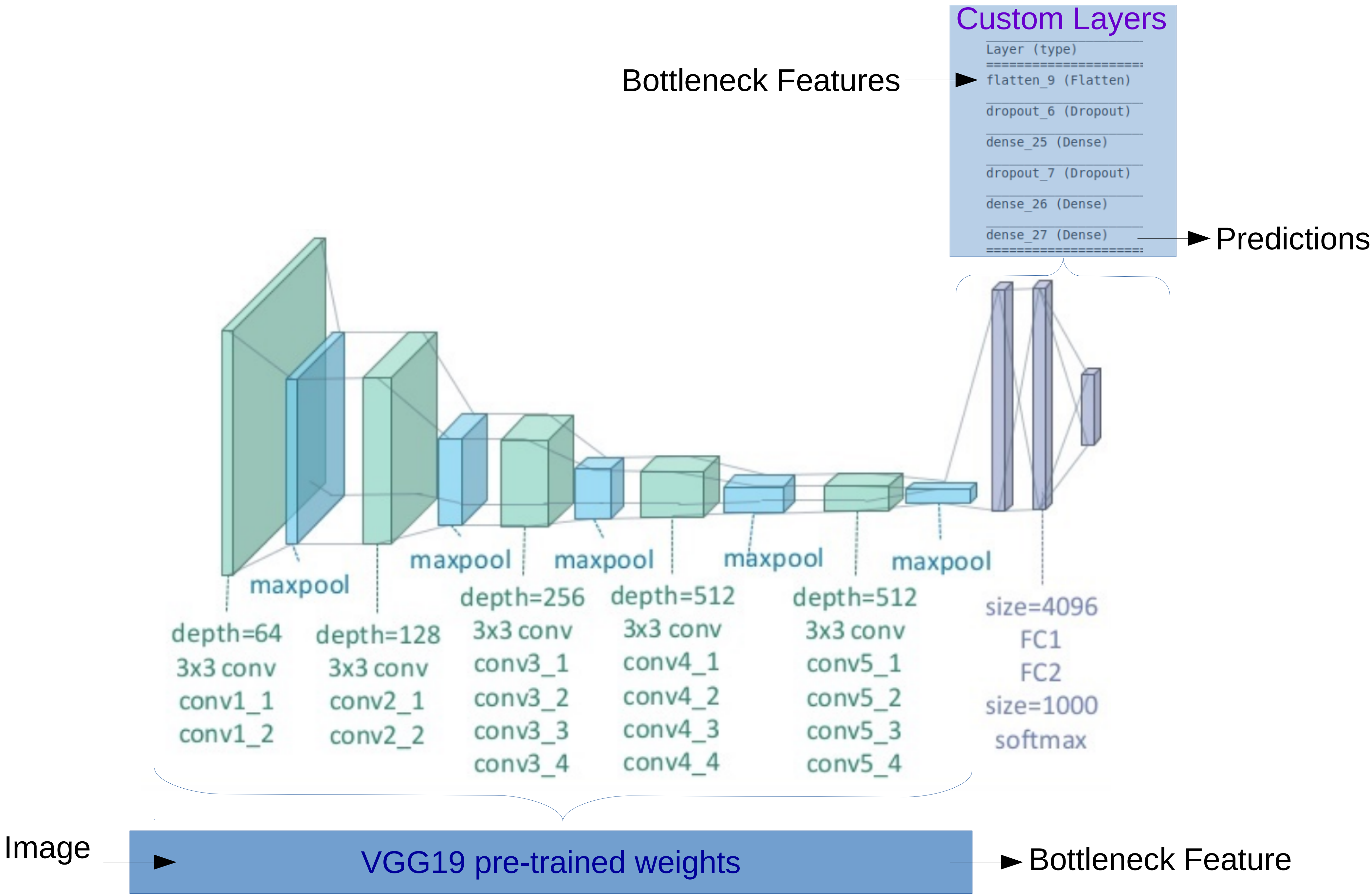


[LeNet-5, LeCun 1980]

Input: Image
Output: Vector indicating image category

In binary classification the output can be just the probability of an image being class 1.

Transfer Learning: Using VGG19



Custom CNN

- 3 convolutional layers.
- Include max-pooling to reduce dimension.
- Include dropout for regularization.
- 3 dense layers.
- 1 output: probability of class 1.

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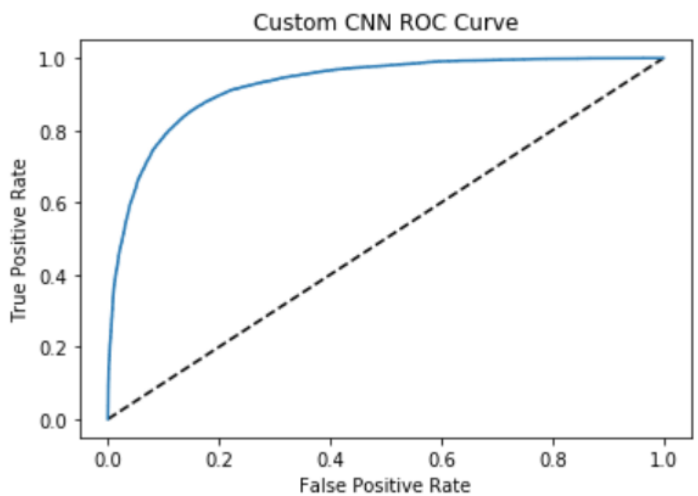
_____________________________
Layer (type)
=============================
conv2d_5 (Conv2D)
_____________________________
max_pooling2d_5 (MaxPooling2
_____________________________
dropout_11 (Dropout)
_____________________________
conv2d_6 (Conv2D)
_____________________________
max_pooling2d_6 (MaxPooling2
_____________________________
dropout_12 (Dropout)
_____________________________
conv2d_7 (Conv2D)
_____________________________
max_pooling2d_7 (MaxPooling2
_____________________________
dropout_13 (Dropout)
_____________________________
flatten_10 (Flatten)
_____________________________
dense_28 (Dense)
_____________________________
dense_29 (Dense)
_____________________________
dense_30 (Dense)
=============================
```

Results

Model	Accuracy	F_1 score (labels 0)	F_1 score (labels 1)
Benchmark naive model	71.38%	83.30	-
Pre-trained VGG19	80.6271%	86.02%	68.45%
Custom CNN	84.9726%	88.95%	76.53%
Custom CNN with image augmentation	84.5220%	88.67%	75.60%

Best model: custom CNN without image augmentation

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Area under ROC: 0.9263
Precision for 0 and 1: 93.63% and 69.19%
Recall for 0 and 1: 84.71% and 85.63%
F1 score for 0 and 1: 88.95% and 76.53%
Confusion matrix:
 [[16642  3004]
 [ 1132  6745]]
```

If user wants false positive rate < 1%:
Threshold: 0.9474

```
Accuracy: 80.69%%
Precision for 0 and 1: 79.16% and 93.36%
Recall for 0 and 1: 99.00% and 35.01%
F1 score for 0 and 1: 87.98% and 50.93%
Confusion matrix:
 [[19450   196]
 [ 5119  2758]]
```

Conclusions

- Transfer learning didn’t perform as well as expected.
- Training the full VGG19 architecture may give better results.
- A custom CNN was proposed. It reaches an accuracy of 84.97%.
- A user can adapt the model to its needs:
  - He can define a threshold to improve accuracy;
  - This will increase the false negative rate;
  - But he can set a range of values defining images needing manual verification.

- In an ideal scenario the proposed model can help the histopathologist to make faster decisions concerning images where the model is certain. This will allow him to focus and spend more time in difficult cases or images were the diagnosis is ambiguous for the machine.