

Segmentation of Breast Cancer Masses in Digital Mammograms: A Convolutional Network Progress Report

Erick Cobos¹

¹Centro de Sistemas Intelligentes
Tecnológico de Monterrey

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Thesis objective

The main goal is to segment breast cancer lesions using convolutional networks, an end-to-end learnable model.

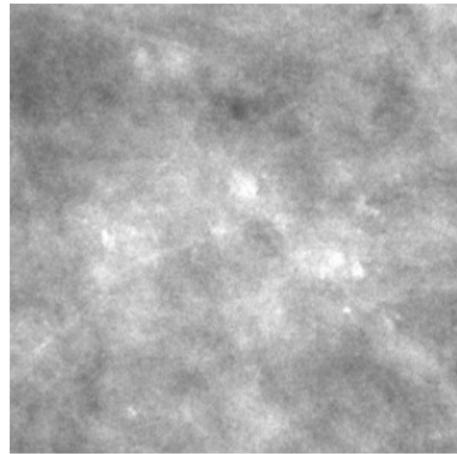
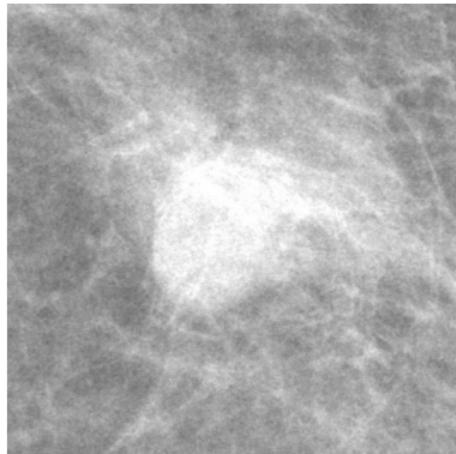
- Obtain and process the mammographic database.
- Develop software to handle the database and train new deep learning models.
- Train modern, fine-tuned convolutional networks.
- Test the viability of convolutional networks for breast cancer research.
- Propose ideas for future research in the area.

Why breast cancer?

Breast cancer is the most commonly diagnosed cancer among women. For women, death rates are the second highest of any cancer. However, survival rate when detected early is close to 100%. On-going project at the institution.

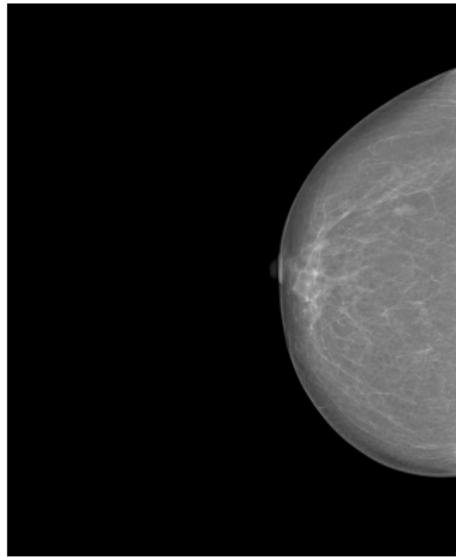
Breast cancer signs

Masses vs. microcalcifications

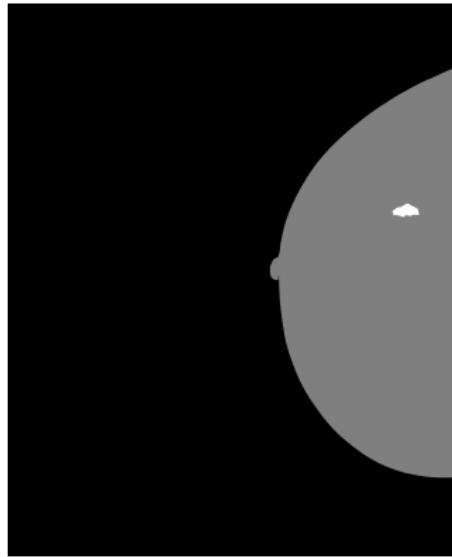


Detection vs. diagnosis

Lesion segmentation



(a) Mammogram



(b) Segmentation

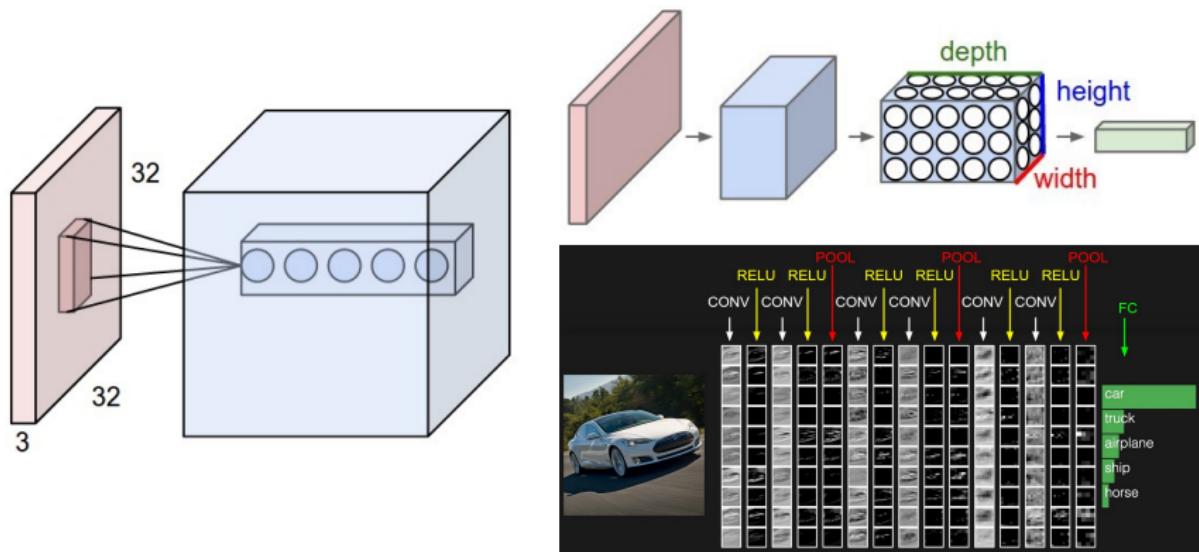
Why convolutional networks?

- Convnets have showed great results in image classification tasks.
- Convnets learn which features are important for the classification.
- We don't need experts to carefully handcraft and select features.

Cons: Need processing power, data.

Convolutional networks

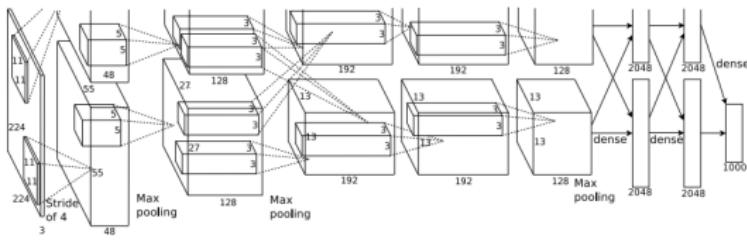
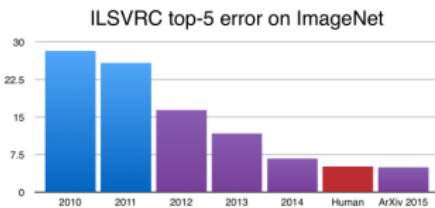
Learnable filters: spatially local and simple in early layers, global and complex in deeper layers.



[Karpathy et al., 2016]

Object classification

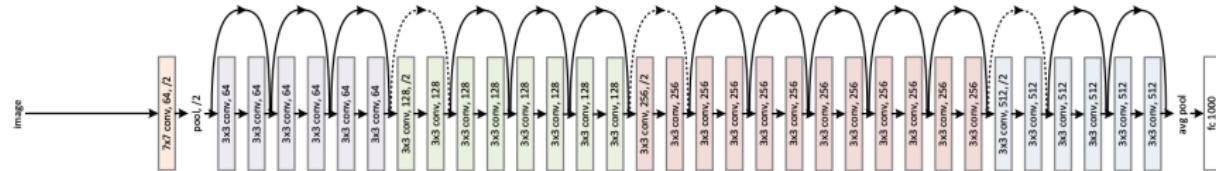
IMAGENET



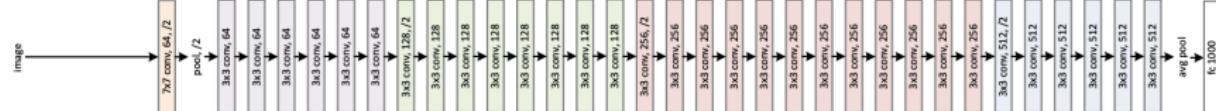
[Nvidia Corp., 2015], [Krizhevsky et al., 2012]

Architectures

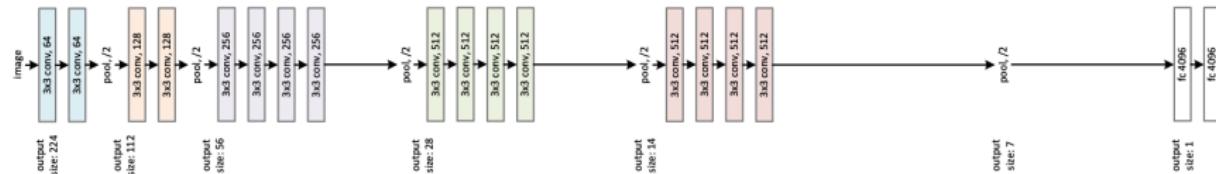
34-layer residual



34-layer plain



VGG-19

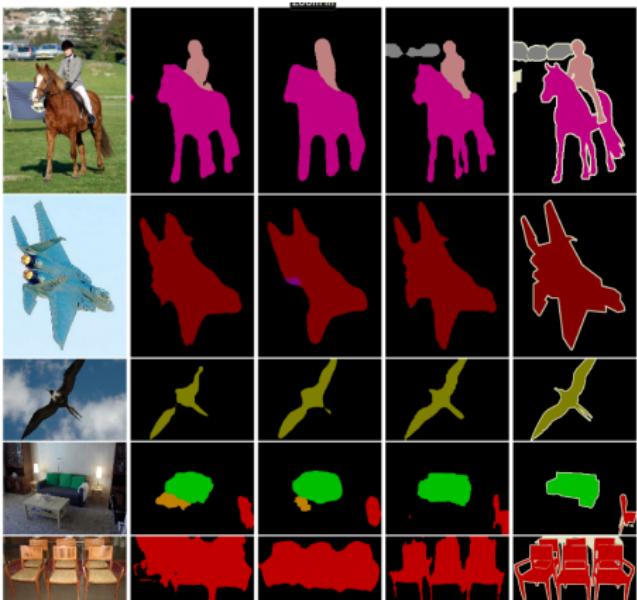
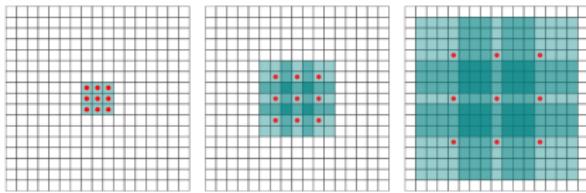
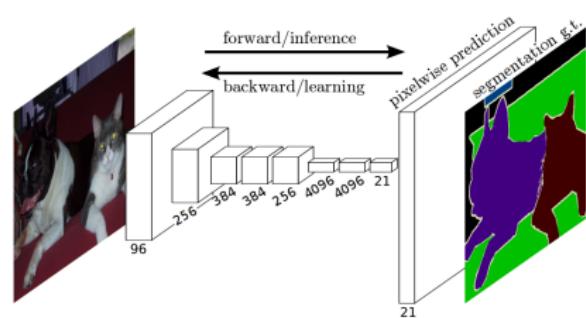


Deeper, no pooling layers, no fully-connected layers, no dropout, all 3x3 kernels, batch normalization, residual connections, attention, memory...

[He et al., 2015]

Segmentation

Solved by upsampling, deconvolution or dilated convolutions.



[Long et al., 2015], [Yu and Koltun, 2016]

Literature review

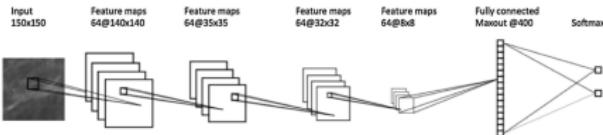


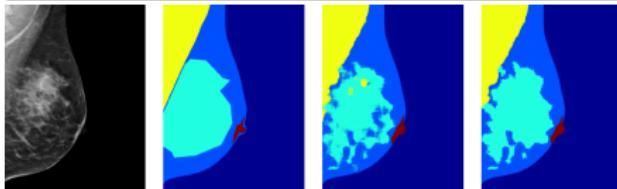
Table 2 – Summary of results in terms of AUC in the test set. Best results are shown in bold typeface and (*) signals scores with no evidence of differences from the highest ($\rho < 0.1$).

Representation	Standalone	Combined with HCfeats
CNN3	0.82 ± 0.03	0.82 ± 0.03 (*)
CNN2	0.76 ± 0.05	0.78 ± 0.04
HGD	0.78 ± 0.04	0.83 ± 0.04
HOG	0.77 ± 0.03	0.81 ± 0.03 (*)
DeCAF	0.79 ± 0.05	0.82 ± 0.03 (*)
HCfeats	0.77 ± 0.02	–

(a) Mass diagnosis (4 layers, 3.4M params)

[Arevalo et al., 2016], [Dubrovina et al., 2015]

Layer	1	2	3	4	5	6	7 - Output
Stage	conv+relu+max	conv+relu+max	conv+relu+max	dropout	full+relu	full+relu	full
# channels	16	16	16	16	128	16	4
Filter size	7 × 7	5 × 5	5 × 5	–	–	–	–
Pooling size	3 × 3	3 × 3	3 × 3	–	–	–	–
Pooling stride	2	2	2	–	–	–	–
Dropout factor	–	–	–	0.5	–	–	–
Spatial input size	61 × 61	27 × 27	11 × 11	3 × 3	3 × 3	1 × 1	1 × 1

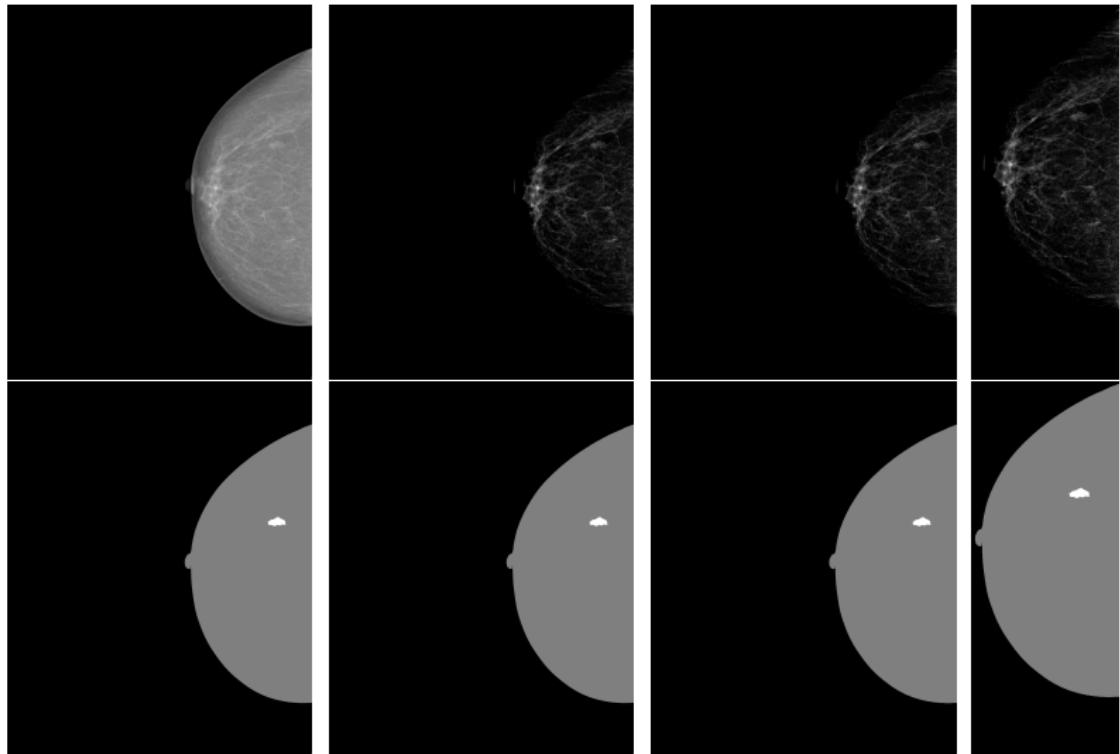


	Pectoral muscle	Fibroglandular tissue	Nipple	Breast tissue (fat, skin)	Average over four tissues
Raw DNN output	0.78	0.60	0.47	0.80	0.66
Post-processed DNN output	0.85	0.61	0.56	0.81	0.71
Raw DNN output, with (x, y) coordinates	0.78	0.60	0.56	0.77	0.68
Post-processed, with (x, y) coordinates	0.79	0.61	0.57	0.77	0.69

Table 2. Average Dice coefficients obtained using the proposed methods for different breast tissues, and average coefficients over the four tissues.

(b) Tissue segmentation (6 layers, 34K params)

Database preprocessing



(a) Original image

(b) Enhancement

(c) Downsampling

(d) Final

Software



TensorFlow

Unwatch ▾ 1

Star 10

Fork 6

```
model_v3.py x
...
# Create filter and biases
filter = tf.Variable(initialize_weights(filter_shape), name='weights')
biases = tf.Variable(tf.zeros([filter_shape[3]]), name='biases')

# Add weights to the weights collection (for regularization)
tf.add_to_collection(tf.GraphKeys.WEIGHTS, filter)

# Perform dilated 2d convolution
w_times_x = tf.nn.atrous_conv2d(input, filter, dilation, padding='SAME')
output = tf.nn.bias_add(w_times_x, biases)

return output

def leaky_relu(x, alpha=0.1):
    """ Leaky ReLU activation function. """
    with tf.name_scope('leaky_relu'):
        output = tf.maximum(tf.mul(alpha, x), x)
    return output

def dropout(x, keep_prob):
    """ performs dropout if training. Otherwise, returns original. """
    output = tf.cond(drop, lambda: tf.nn.dropout(x, keep_prob), lambda: x)
    return output

# Create a batch with a single image
batch = tf.expand_dims(image, 0)

# Define the architecture
with tf.name_scope('conv1'):
    conv = conv_op(batch, [6, 6, 1, 32], [1, 2, 2, 1])
    relu = leaky_relu(conv)
    conv1 = dropout(relu, keep_prob=0.9)
with tf.name_scope('conv2'):
    conv = conv_op(conv1, [3, 3, 32, 32])
    relu = leaky_relu(conv)
    conv2 = dropout(relu, keep_prob=0.9)

with tf.name_scope('conv3'):
    conv = conv_op(conv2, [3, 3, 32, 64], [1, 2, 2, 1])
    relu = leaky_relu(conv)
    conv3 = dropout(relu, keep_prob=0.8)
```

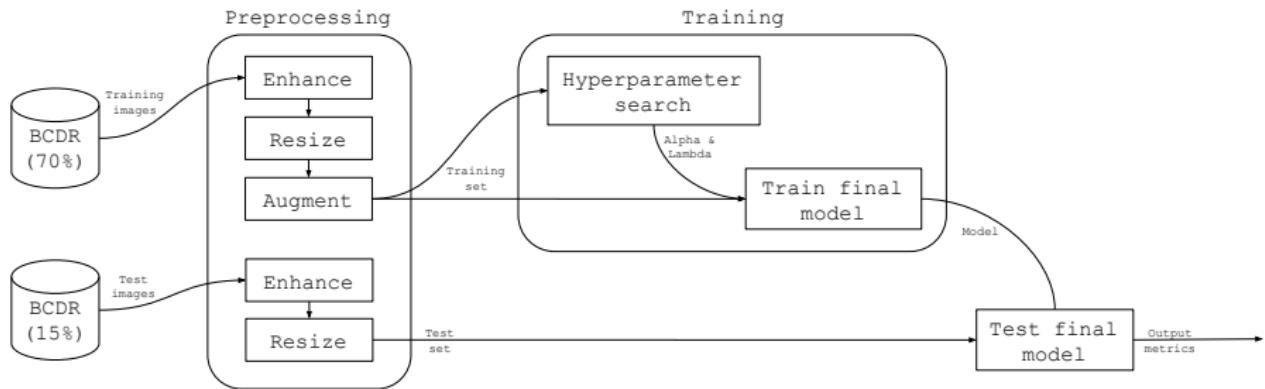
Python ▾

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Overview of the solution



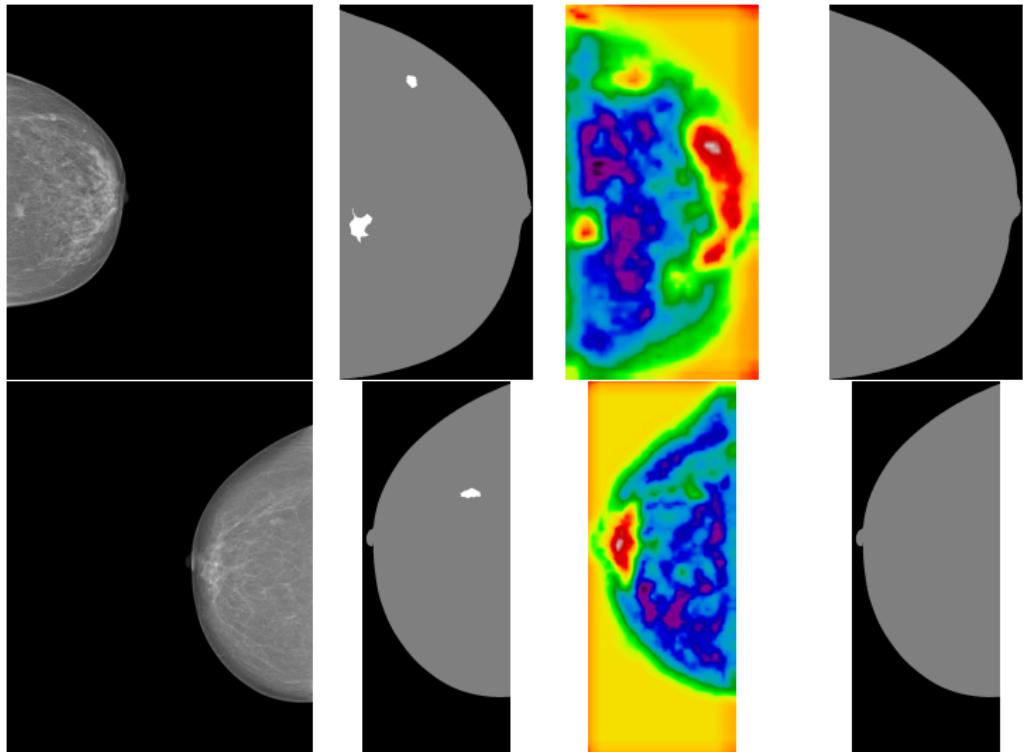
Experiment 1

Modelled on a VGG network, winner of the 2014 ImageNet.

Layer	Filter	Stride	Pad	Volume	Parameters
INPUT	-	-	-	$112 \times 112 \times 1$	-
CONV -> Leaky RELU	6×6	2	2	$56 \times 56 \times 56$	2 072
CONV -> Leaky RELU	3×3	1	1	$56 \times 56 \times 56$	28 280
MAXPOOL	2×2	2	0	$28 \times 28 \times 56$	-
CONV -> Leaky RELU	3×3	1	1	$28 \times 28 \times 84$	42 420
CONV -> Leaky RELU	3×3	1	1	$28 \times 28 \times 84$	63 588
MAXPOOL	2×2	2	0	$14 \times 14 \times 84$	-
CONV -> Leaky RELU	3×3	1	1	$14 \times 14 \times 112$	84 784
CONV -> Leaky RELU	3×3	1	1	$14 \times 14 \times 112$	113 008
CONV -> Leaky RELU	3×3	1	1	$14 \times 14 \times 112$	113 008
MAXPOOL	2×2	2	0	$7 \times 7 \times 112$	-
FC -> Leaky RELU	7×7	1	3	$7 \times 7 \times 448$	2 459 072
FC	1×1	1	0	$7 \times 7 \times 1$	449
BILINEAR (x16)	-	-	-	$112 \times 112 \times 1$	-

IOU	F1-score	G-mean	Accuracy	Sensitivity	Specificity	Precision	Recall
0.109	0.197	0.49	0.98	0.243	0.987	0.165	0.243

Qualitative results



(a) Original

(b) Label

(c) Prediction

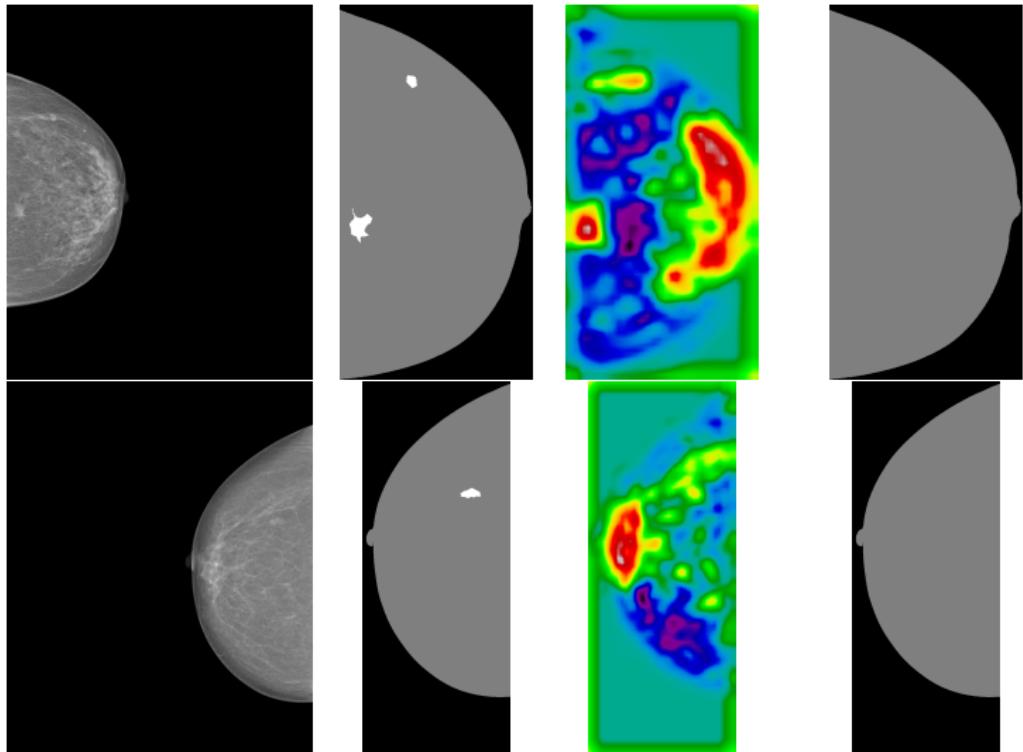
(d) Segmentation

Experiment 2

To combat class imbalance, we use a loss function that weights errors over breast masses higher than errors over breast tissue. Architecture as in Experiment 1.

IOU	F1-score	G-mean	Accuracy	Sensitivity	Specificity	Precision	Recall
0.117	0.21	0.493	0.981	0.246	0.989	0.184	0.246

Qualitative results



(a) Original

(b) Label

(c) Prediction

(d) Segmentation

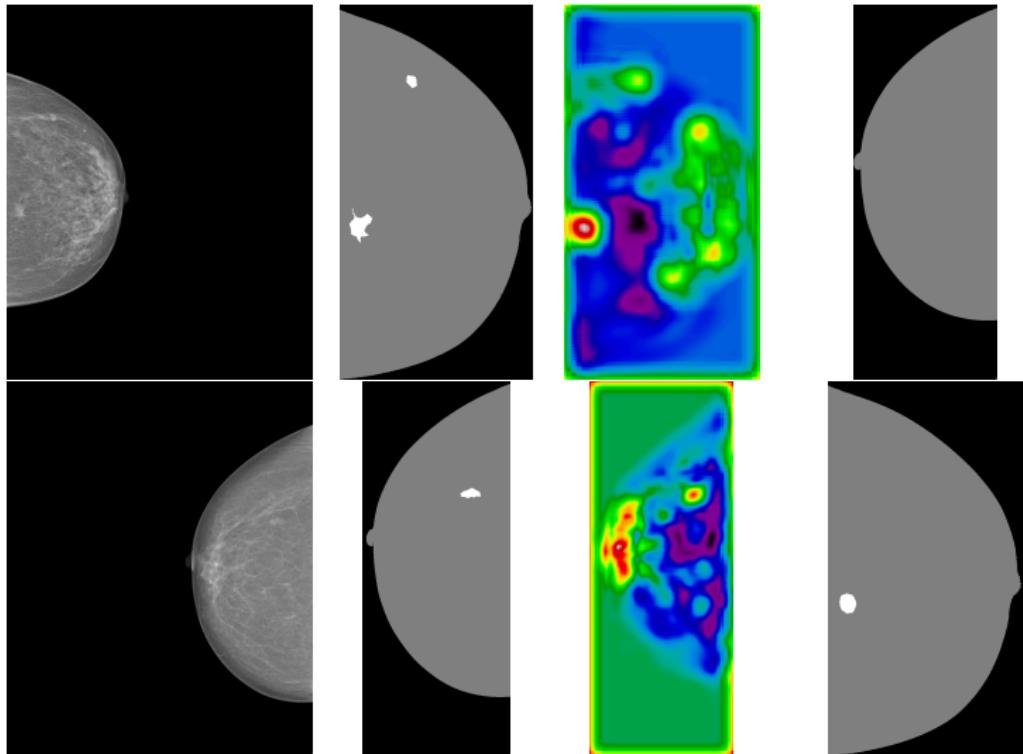
Experiment 3

Modelled on the Residual network, winner of the 2015 ImageNet. Deeper, fewer parameters and better resolution (4x).

Layer	Filter	Stride	Pad	Dilation	Volume	Parameters
INPUT	-	-	-	-	$128 \times 128 \times 1$	-
CONV -> LRELU	6×6	2	2	1	$64 \times 64 \times 32$	1 184
CONV -> LRELU	3×3	1	1	1	$64 \times 64 \times 32$	9 248
CONV -> LRELU	3×3	2	1	1	$32 \times 32 \times 64$	18 496
CONV -> LRELU	3×3	1	1	1	$32 \times 32 \times 64$	36 928
CONV -> LRELU	3×3	1	2	2	$32 \times 32 \times 128$	73 856
CONV -> LRELU	3×3	1	2	2	$32 \times 32 \times 128$	147 584
CONV -> LRELU	3×3	1	2	2	$32 \times 32 \times 128$	147 584
CONV -> LRELU	3×3	1	2	2	$32 \times 32 \times 128$	147 584
CONV -> LRELU	3×3	1	4	4	$32 \times 32 \times 256$	295 168
CONV	8×8	1	14	4	$32 \times 32 \times 1$	16 385
BILINEAR (x4)	-	-	-	-	$128 \times 128 \times 1$	-

IOU	F1-score	G-mean	Accuracy	Sensitivity	Specificity	Precision	Recall
-	-	-	-	-	-	-	-

Qualitative results



(a) Original

(b) Label

(c) Prediction

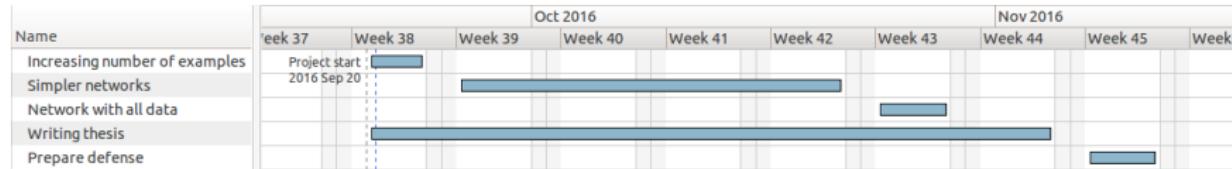
(d) Segmentation

Writing the thesis

60 pages and counting...

Future work

- Train networks with increasing number of examples
- Train simpler networks with no preprocessing or bell and whistles
- Train a final network with all data
- Write thesis
- Prepare thesis defense



Conclusion

- A convolutional network can be used as an end-to-end trainable system to perform segmentation of mammograms.
- Advances in segmentation of real-life images translate to mammographic images.
- Fine-tuning is necessary to find a good local minimum.
- Different architectures can improve results, although small variations are not as important.
- Training medium networks is feasible with the available resources.

Yet to answer:

- Is the bottleneck for learning the network architecture or the amount of data?
- Are convolutional networks a good option for future research?

