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

Progress Report

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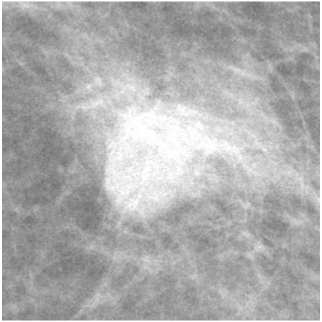
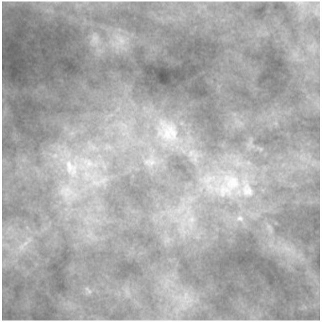
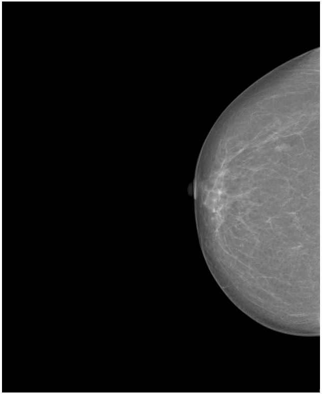
Masses vs. microcalcifications

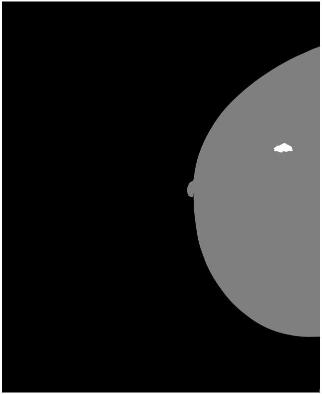
 

Detection vs. diagnosis

Lesion segmentation

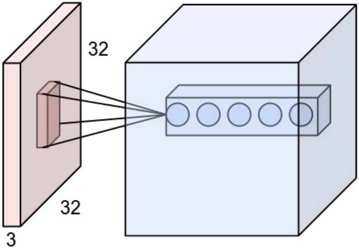


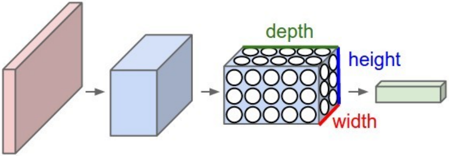
(a) Mammogram

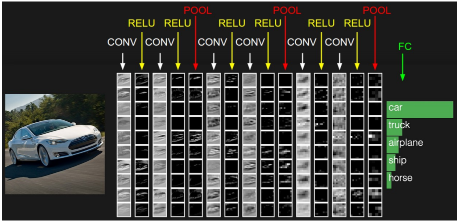


(b) Segmentation

Convolutional networks

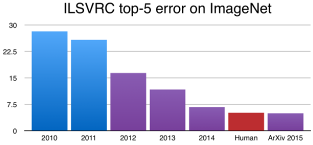


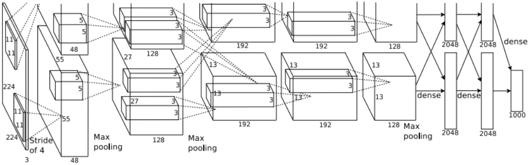




[Karpathy et al., 2016]

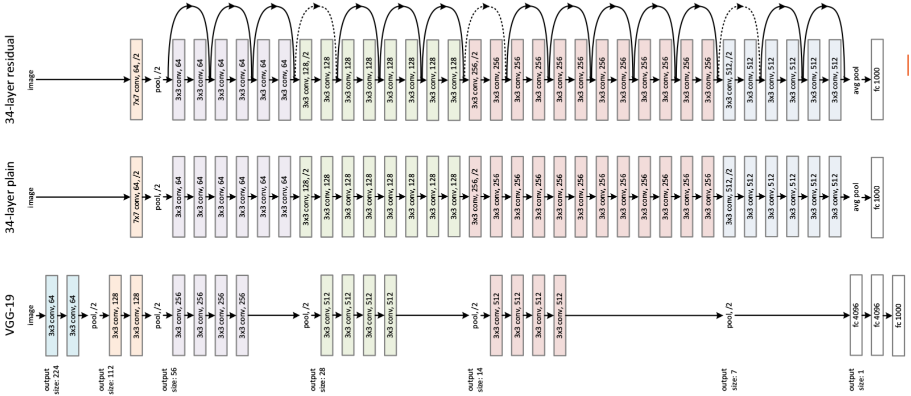
What have they done





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

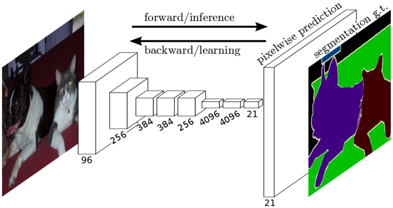
Architectures

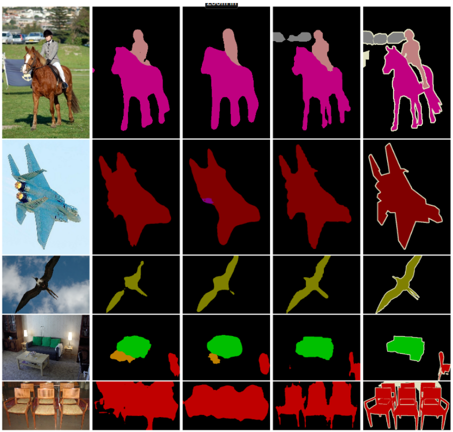


Deeper, no pooling layers, no fully-connected layers, no dropout, all 3x3 kernels, batch normalization, residual connections,...

[He et al., 2015]

Solved by upsampling, deconvolution or dilated convolutions.





(a) Image (b) FCN-8s (c) DeepLab (d) Our front end (e) Ground truth

[Longet al., 2015], [Yu and Koltun, 2016]

Literature review

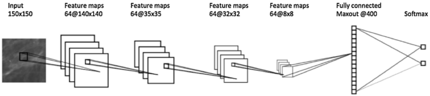
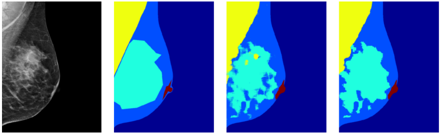


Table 2 – Summary of results in terms of AUC in the test set. Best results are shown in bold typeface and (*) signals scores with no evidence of differences from the highest ($\rho < 0.1$).

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)

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



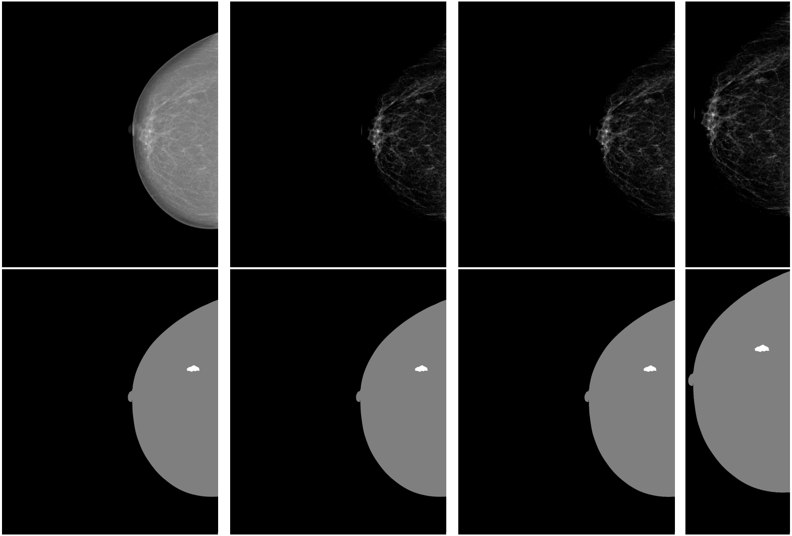
	Pectoral muscle	Fibroglandular tissue	Nipple	Breast tissue (fat, skin)	Average over four tissues
Raw DNN output	0.78	0.60	0.47	0.80	0.66
Post-processed DNN output	0.85	0.61	0.56	0.81	0.71
Raw DNN output, with (x, y) coordinates	0.78	0.60	0.56	0.77	0.68
Post-processed, with (x, y) coordinates	0.79	0.61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

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

Database preprocessing



(a) Original image (b) Enhancement (c) Downsampling (d) Final

Software

model_v3.py

```python
    """
    # 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)
```

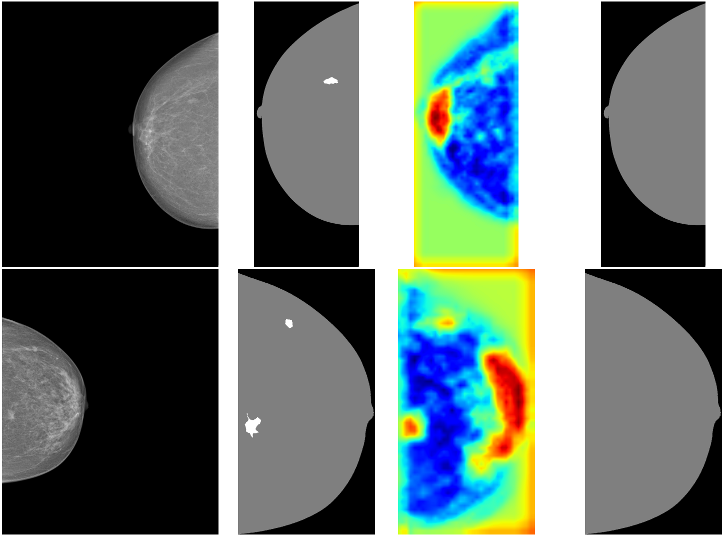
Python ▾ Tab Width: 4 ▾ Ln 49, Col 14 INS

Experiment 1

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
0.022	0.031	0.038	0.975	0.028	0.982	0.040	0.028

Qualitative results



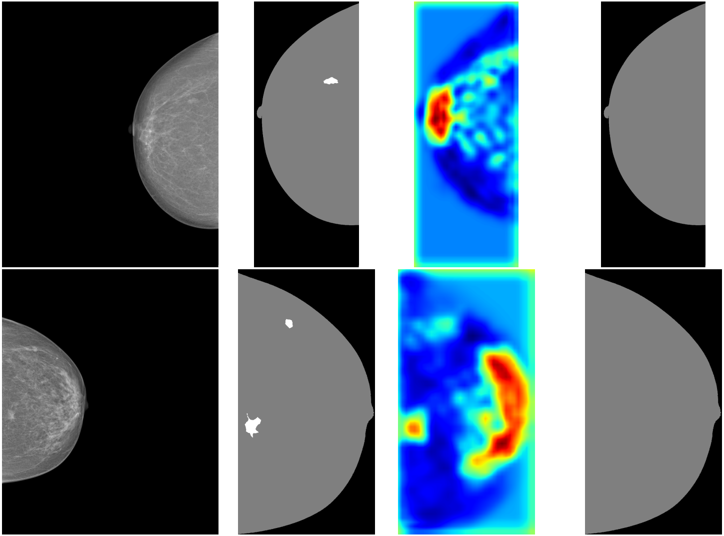
(a) Original (b) Label (c) Prediction (d) Segmentation

Experiment 2

Weighted loss function.

IOU	F1-score	G-mean	Accuracy	Sensitivity	Specificity	Precision	Recall
0.028	0.041	0.071	0.967	0.046	0.973	0.052	0.046

Qualitative results



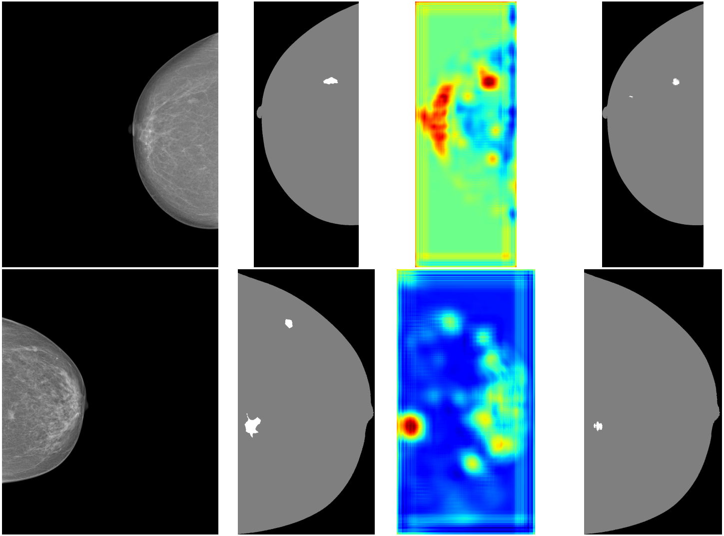
(a) Original (b) Label (c) Prediction (d) Segmentation

Experiment 3

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

65 pages...

Future work

- Write the thesis
- ?

Questions