

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

Master's thesis

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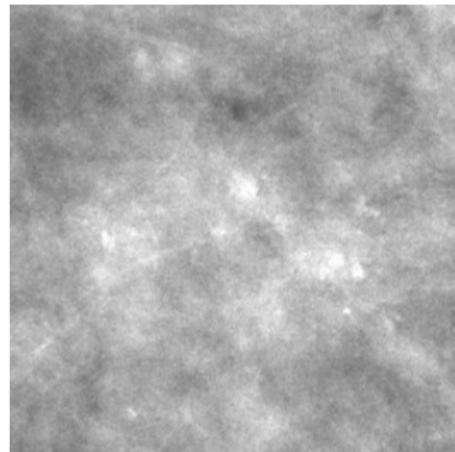
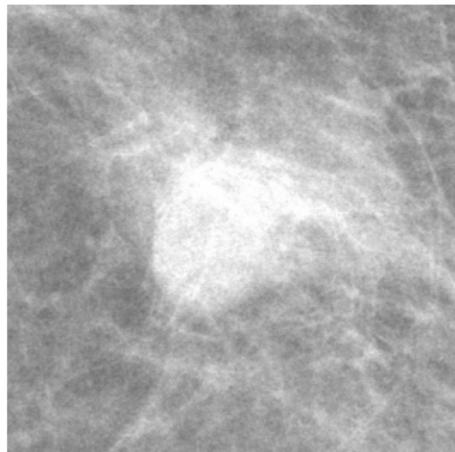
Thesis objective

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.
- Develop and train modern, fine-tuned convolutional networks.
- Test the viability of convolutional networks for breast cancer research through different experiments.
- Propose ideas for future research in the area.

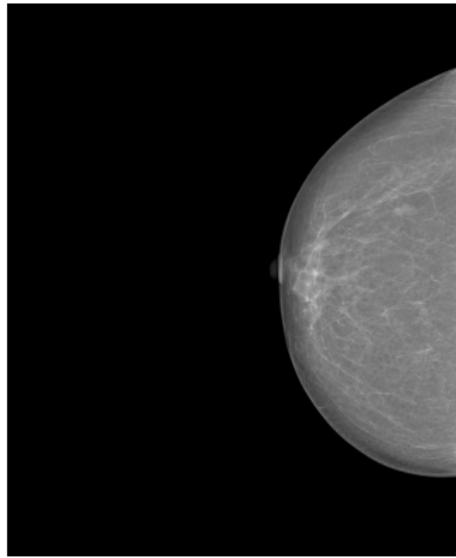
Breast cancer signs

Masses vs. microcalcifications

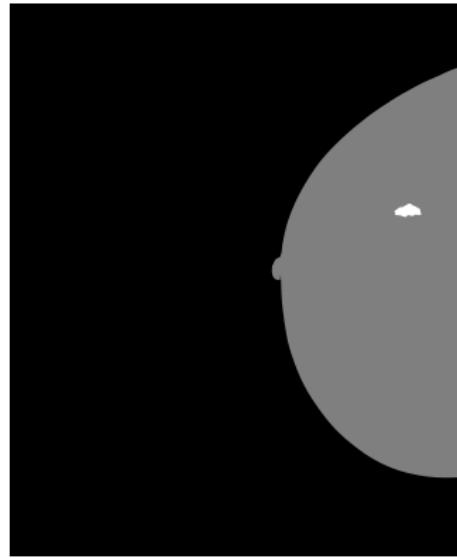


Detection vs. diagnosis

Lesion segmentation



(a) Mammogram



(b) Segmentation

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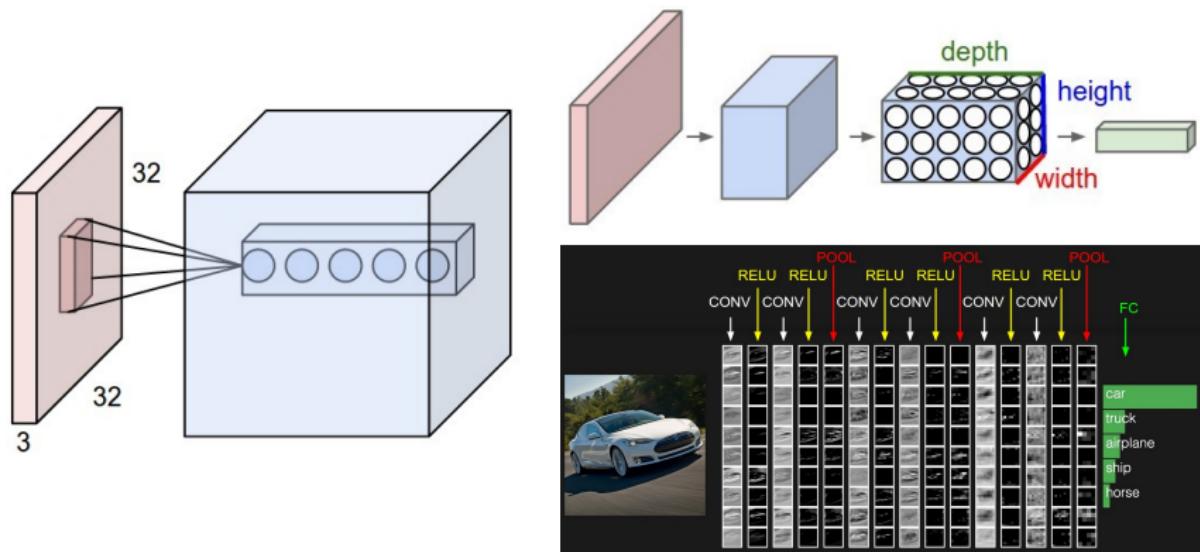
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Convolutional networks

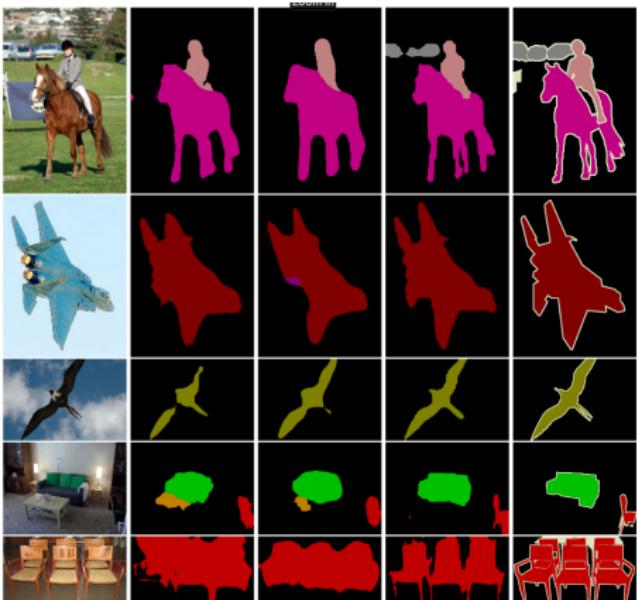
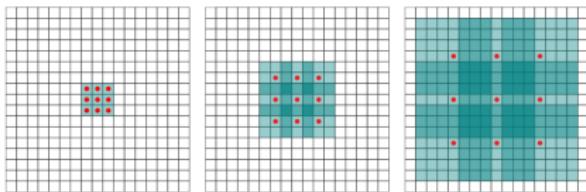
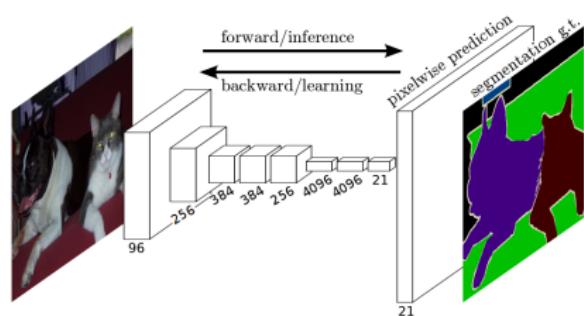
Learnable filters: spatially local and simple in early layers, global and complex in deeper layers.



[Karpathy et al., 2016]

Segmentation

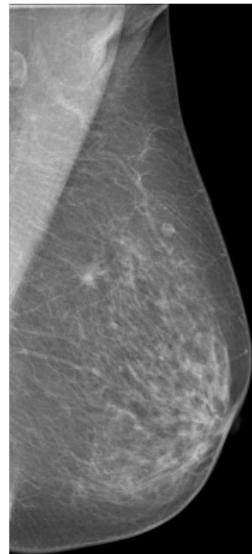
Solved by upsampling, deconvolution or dilated convolutions.



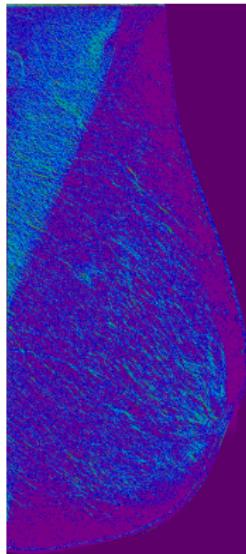
[Long et al., 2015], [Yu and Koltun, 2016]

Example

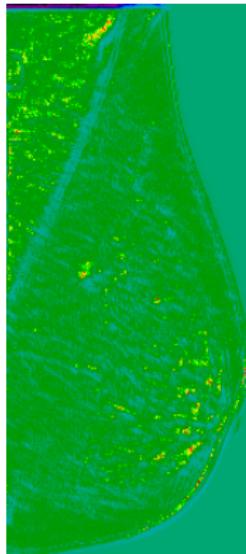
Selected feature maps from different layers.



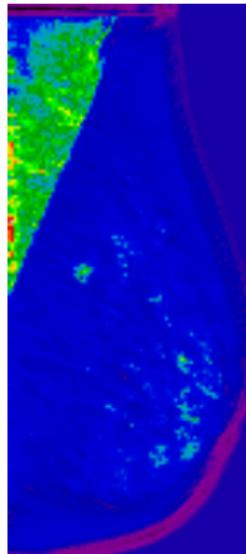
(a) Input
 (1408×624)



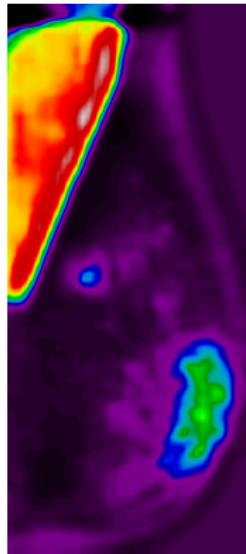
(b) Layer 1
 (704×312)



(c) Layer 4
 (352×156)



(d) Layer 7
 (176×78)



(e) Output
 (1408×624)

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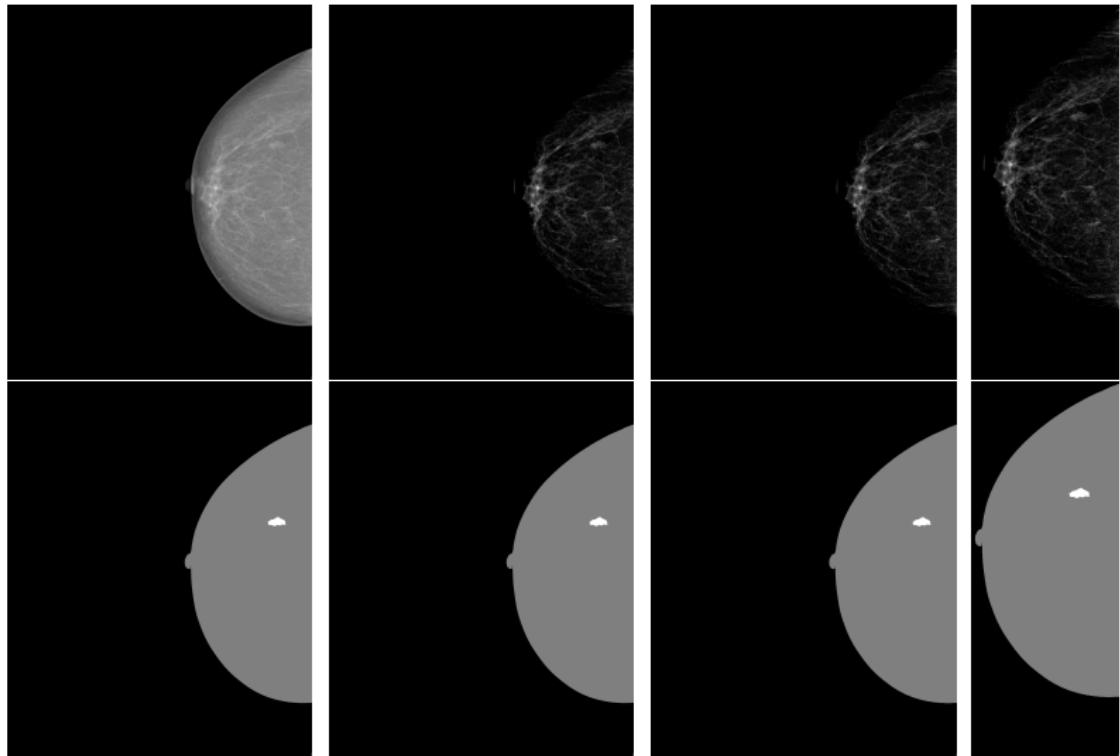
Database

Our mammographic database provided by the Breast Cancer Digital Repository Consortium consists of 256 digital mammograms from 63 portuguese patients with at least one breast mass.

We augment the data set for training.

	Patients		Mammograms		Masses	
	Training	Test	Training	Test	Training	Test
Fold 1	50	13	189	67	106	33
Fold 2	50	13	209	47	112	27
Fold 3	50	13	204	52	110	29
Fold 4	51	12	209	47	110	29
Fold 5	51	12	213	43	118	21
Average	50.6	12.6	204.8	51.2	111.2	27.8

Preprocessing



(a) Original image

(b) Enhancement

(c) Downsampling

(d) Final

Software



TensorFlow

Unwatch ▾

1

★ Star

14

Fork

11

```
model_v3.py x

# Do mirror padding (to deal better with borders)
padded_input = pad_atrous_input(input, filter_shape, dilation)

# Perform dilated 2d convolution
w_times_x = tf.nn.atrous_conv2d(padded_input, filter, dilation,
                                padding='VALID')
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

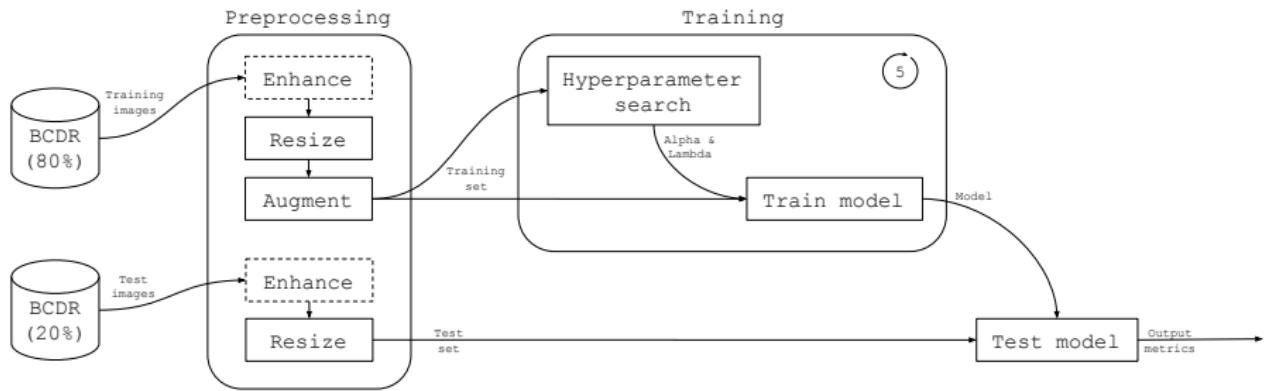
def dropout(x, keep_prob):
    """ Performs dropout if training. Otherwise, returns original. """
    output = tf.cond(drop, lambda: tf.nn.dropout(x, keep_prob), lambda: x)
    return output

# 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)
with tf.name_scope('conv4'):
    conv = conv_op(conv3, [3, 3, 64, 64])
    relu = leaky_relu(conv)
    conv4 = dropout(relu, keep_prob=0.8)
```

Overview of the solution



Model 1

Simple architecture (206K parameters). Three configurations tested: no enhancement + no weighted loss, no enhancement + weighted loss and enhancement + weighted loss.

Layer	Filter	Stride	Pad	Dilation	Volume	Parameters
INPUT	-	-	-	-	$52 \times 52 \times 1$	-
CONV -> RELU	5×5	2	2	1	$26 \times 26 \times 32$	832
CONV -> RELU	3×3	1	1	1	$26 \times 26 \times 32$	9 248
CONV -> RELU	3×3	2	1	1	$13 \times 13 \times 64$	18 496
CONV -> RELU	3×3	1	1	1	$13 \times 13 \times 64$	36 928
CONV -> RELU	3×3	1	2	2	$13 \times 13 \times 96$	55 392
CONV -> RELU	3×3	1	2	2	$13 \times 13 \times 96$	83 040
CONV	5×5	1	6	3	$13 \times 13 \times 1$	2 401
BILINEAR (x4)	-	-	-	-	$52 \times 52 \times 1$	-

Model 2

Modelled on a VGG network, winner of the 2014 ImageNet. Does not use dilation. Tested with no enhancement + weighted loss.

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)	-	-	-	$112 \times 112 \times 1$	-

Model 3

Modelled on the Residual network, winner of the 2015 ImageNet. Deeper, fewer parameters and better resolution (4x). Tested with enhancement + weighted loss.

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)	-	-	-	-	$128 \times 128 \times 1$	-

Training

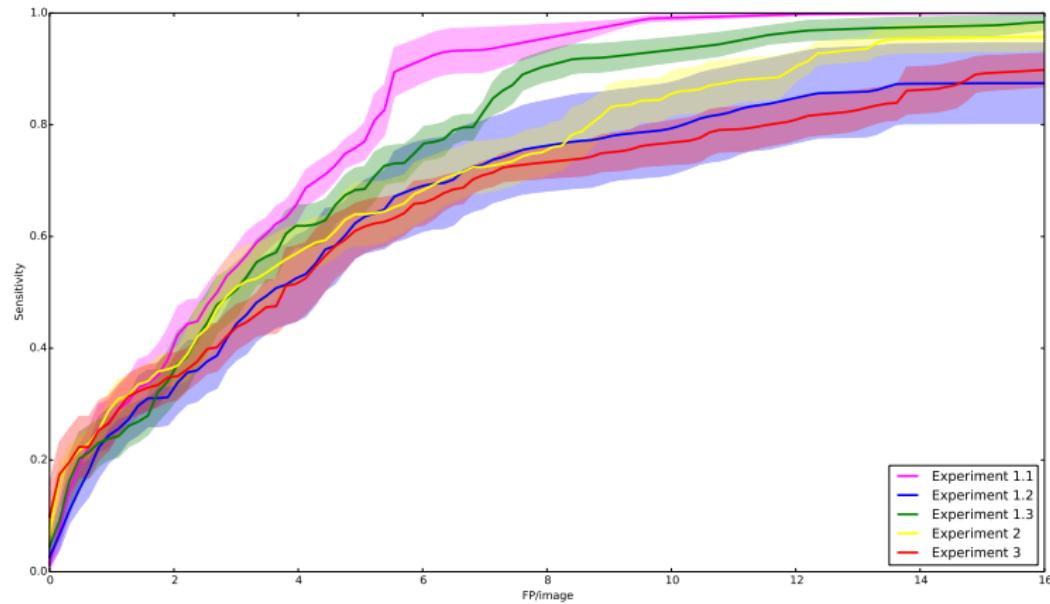
Hyperparameter search: For each fold, we train 25 networks with different learning rate and regularization parameters to select the best combination. We hold out 20% of the training set for evaluation.

Training: We trained the final models for 30 epochs using ADAM. Convergence was achieved.

Evaluation: We use 5-fold cross-validation to generate our results and variability estimates.

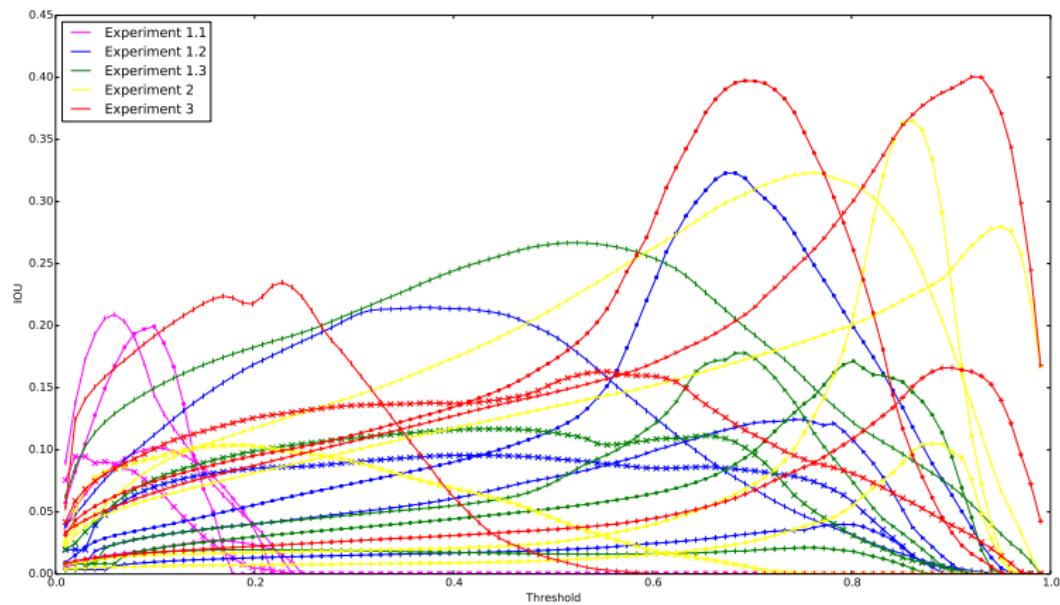
FROC curves

Free-response ROC curves plot the sensitivity of the system against the number of false predictions per image. Shading shows one standard error of the mean.



IOU curves

Intersection-over-union as the threshold is varied. Each line is one fold.

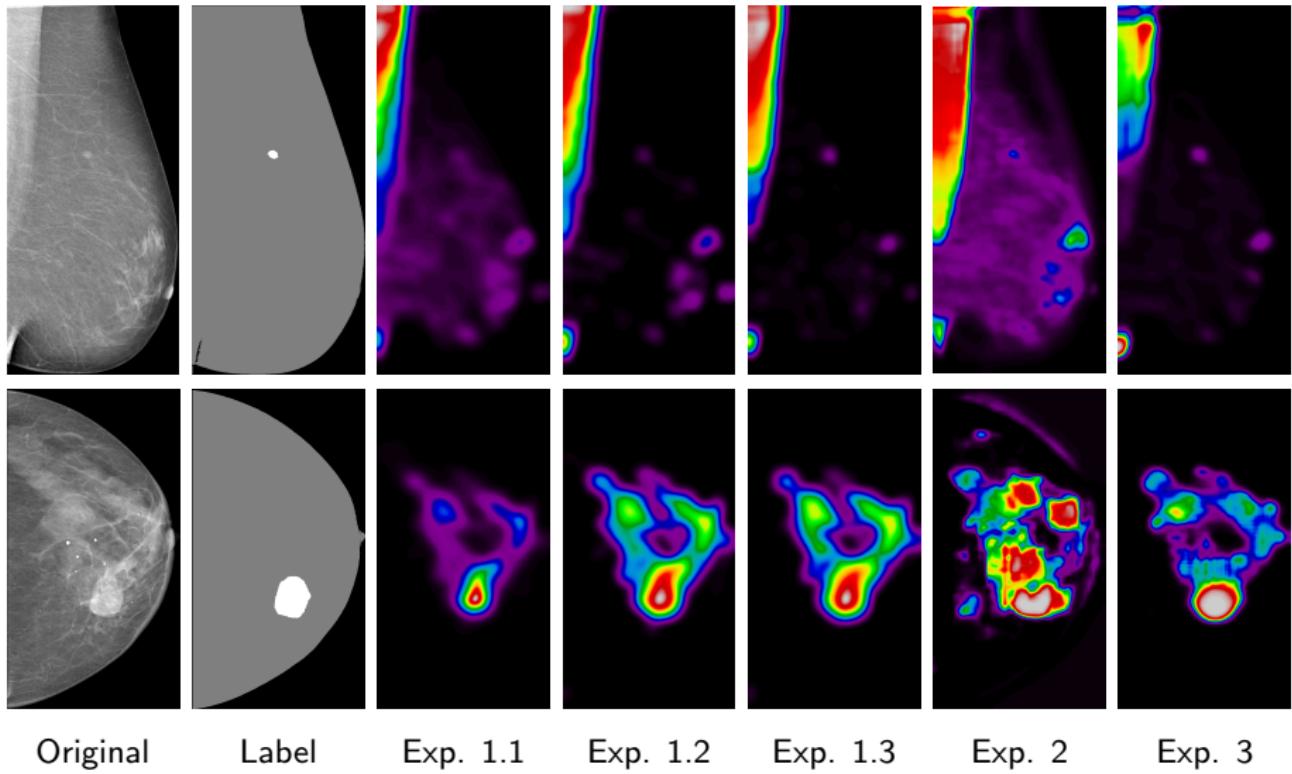


Peak IOU

IOU value for the best threshold per fold.

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Average \pm SEM
Experiment 1.1	0.03	0.09	0.21	0.20	0.10	0.13 ± 0.03
Experiment 1.2	0.04	0.10	0.21	0.32	0.12	0.16 ± 0.04
Experiment 1.3	0.02	0.12	0.27	0.17	0.18	0.15 ± 0.04
Experiment 2	0.11	0.10	0.32	0.37	0.28	0.24 ± 0.05
Experiment 3	0.17	0.17	0.23	0.40	0.40	0.27 ± 0.05
Average	0.07	0.11	0.25	0.29	0.22	

Qualitative results



Original

Label

Exp. 1.1

Exp. 1.2

Exp. 1.3

Exp. 2

Exp. 3

Qualitative results

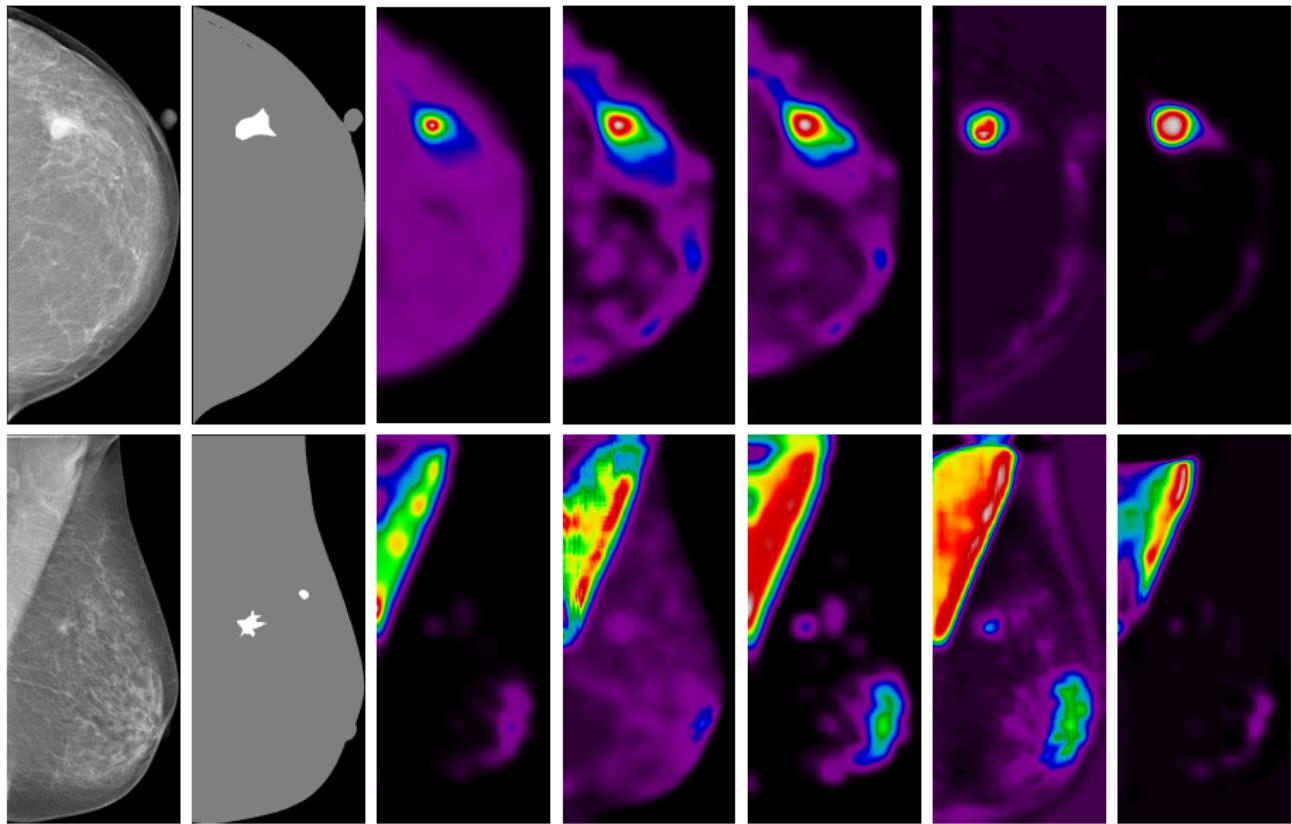


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Conclusion

- Convolutional networks can be used as an end-to-end trainable system to perform segmentation of mammograms.
- Small architectural variations are irrelevant as long as the architecture is flexible enough.
- Using a weighted loss function improves performance whereas enhancement helps only slightly.
- Hyperparameter fine-tuning is necessary to find a good minimum.
- The bottleneck for learning seems to be the small data sets.
- Training small-to-medium networks is feasible with the available resources.
- Convolutional networks remain a promising option for future medical imaging research.

Contributions

- First reported use of convolutional networks for breast cancer lesion segmentation.
- Small, modern architectures tailored to segmentation.
- Mammographic data set and preprocessing tools.
- Software for designing, training and evaluating convolutional networks.
- Support to other deep learning projects in the campus.

Future work

- Create a high-quality, large data set.
- Curate data by deleting obvious lesions, benign lesions and chest muscle, labelling other kind of lesions and breast tissue or joining images from different sources.
- Validate results using different architectures and bigger data sets.
- Use standard computer vision features as input to the network.
- Incorporate current trends to newer architectures.
- Develop standard evaluation metrics for these kind of predictions.

