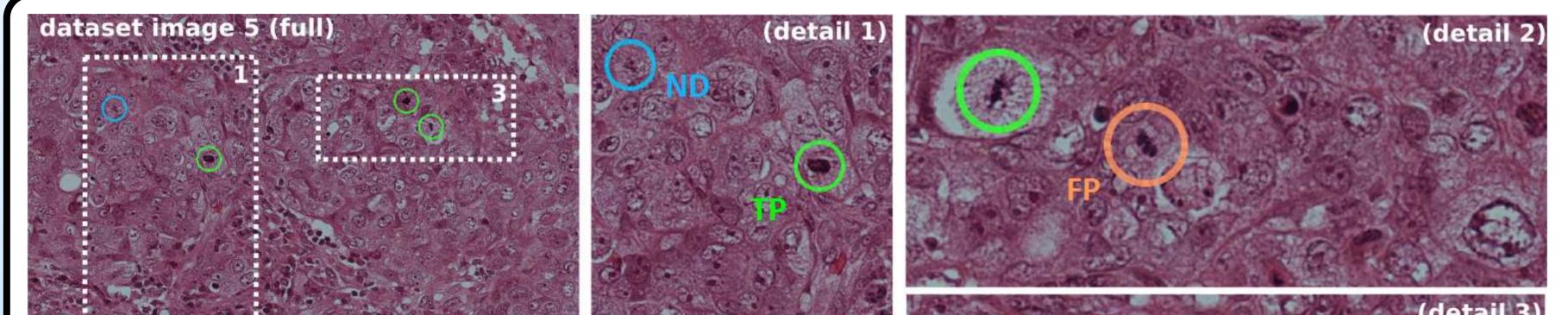


# **Mitosis Detection in Breast Cancer Histology Images with Deep Neural Networks**



Dan C. Cireşan, Alessandro Giusti, Luca M. Gambardella, Jürgen Schmidhuber IDSIA, USI and SUPSI, Lugano, Switzerland – {dan, alessandrog, luca, juergen}@idsia.ch

We describe the method that won the ICPR 2012 Mitosis Detection Competition, outperforming other methods by a significant margin. We use deep max-pooling convolutional neural networks to detect mitosis in breast histology images. The networks are trained to classify each pixel in the images, using as context a patch centered on the pixel. Simple postprocessing is then applied to the network output. New: the same method also won the first place at MICCAI 2013 Grand Challenge: Assessment of Mitosis Detection Algorithms

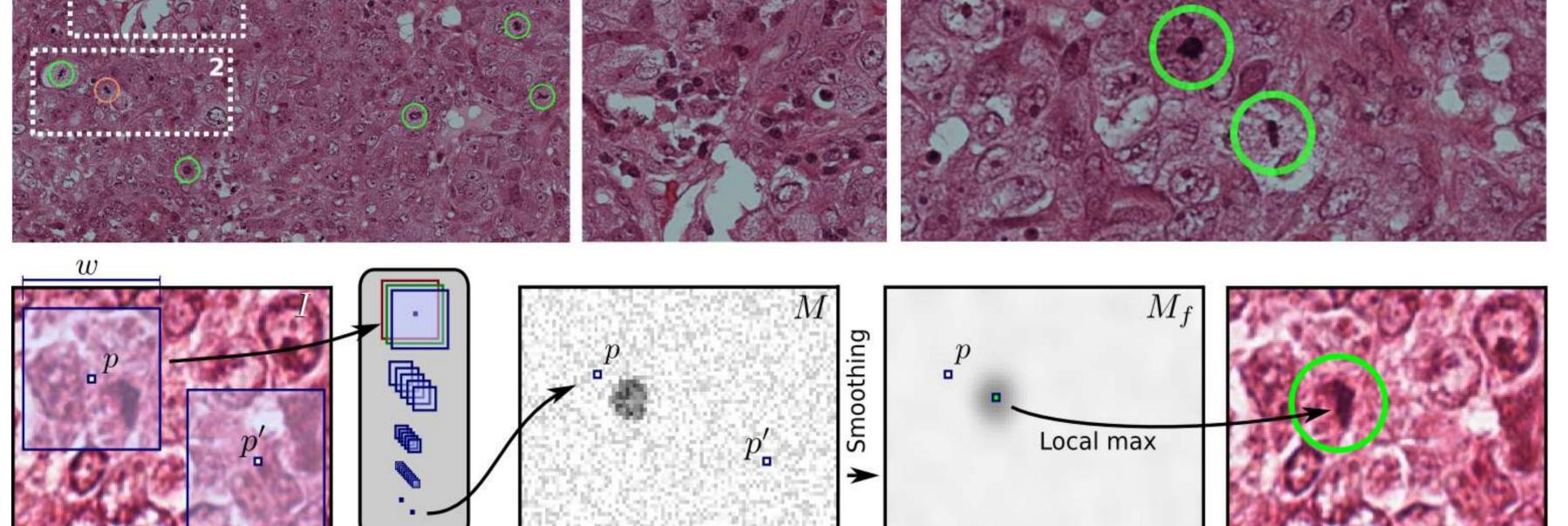


## **Deep Neural Networks (DNN) trained on GPU**

- 4 x NVIDIA GTX 580 1.5GB RAM, more than 6 TFLOPS (maximum theoretical speed)
- 50x speed-up compared with a single threaded CPU version of the DNN program (one day on GPU vs two months on CPU)



Training each net requires ~1 day. Less



Original RGB Image

Pr(p is close to a mitosis centroid)

**Method.** Given an input RGB image, the problem is to find a set of detections, each reporting the centroid coordinates for a single mitosis. The problem is solved by training a detector on training images with given ground truth information about the centroid of each visible mitosis. Each pixel is assigned one of two possible classes, mitosis or non-mitosis, the former to pixels at (or close to) mitosis centroids, the latter to all other pixels. For any given pixel p, the DNN predicts its class using raw RGB values in a square image window centered on p.

than 30 epochs are needed to minimize error on validation data

Detecting mitosis in a single 4 Mpixel image requires ~8 minutes with our MATLAB implementation (see ICIP 2013)

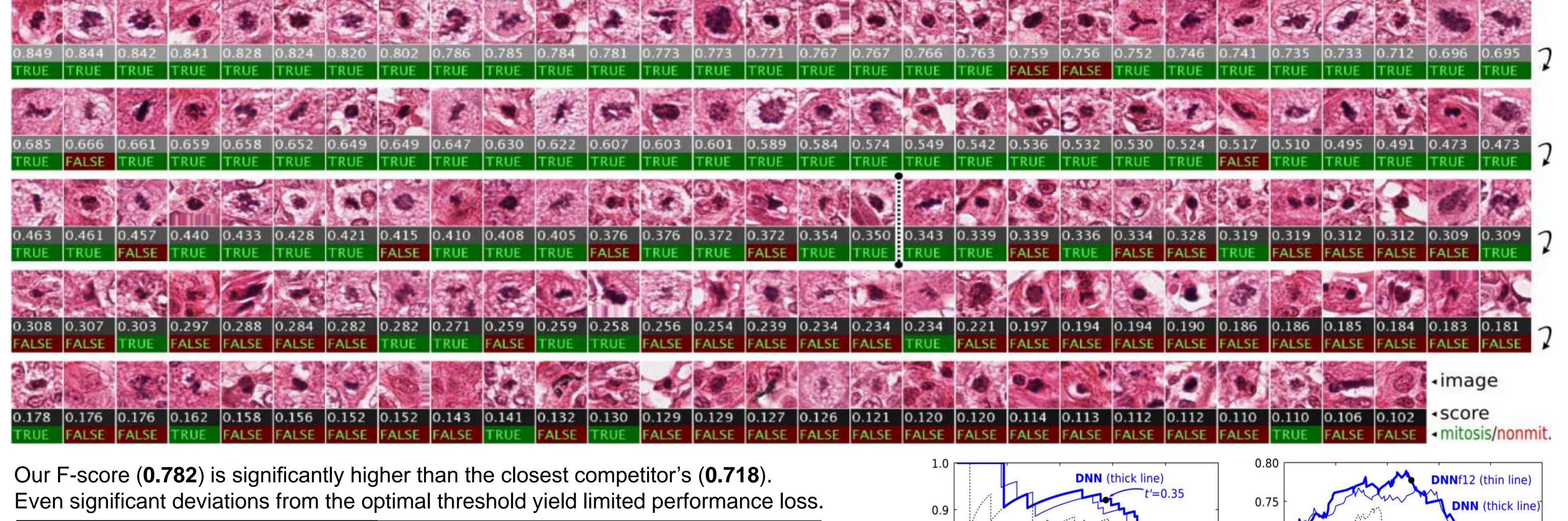
# **Network Architectures**

I – input C – convolutional MP – max-pooling FC – fully connected

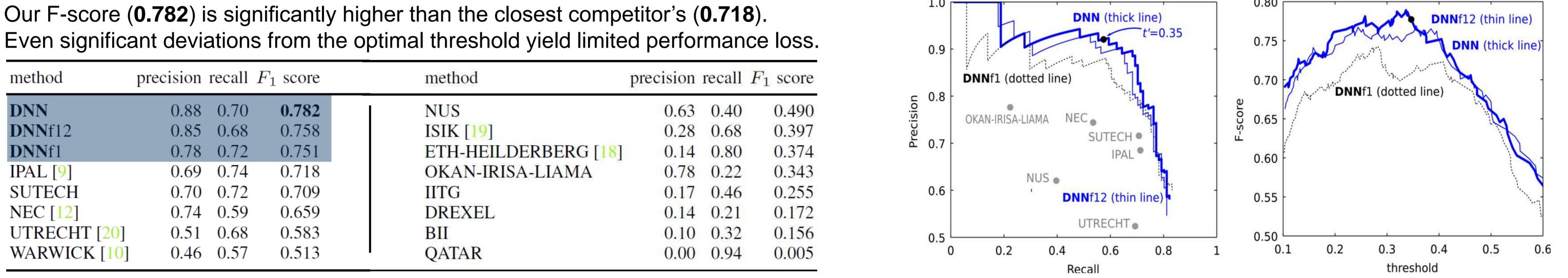
Connections	Weights			r Type	Layer	Connections	Weights	Filter size	Maps and neurons	Туре	Layer
		size	and neurons			_	_	_	3M x 101x101N	I	0
s			3M x 101x101N	I	0	2080000	208	2x2	16M x 100x100N	С	1
7529536	784	4x4	16M x 98x98N	C	1		—	2x2	16M x 50x50N	MP	2
a	<del></del>	2x2	16M x 49x49N	MP	2	5345280	2320	3x3	16M x 48x48N	С	3
8700992	4112	4x4	16M x 46x46N	С	3		—	2x2	16M x 24x24N	MP	4
8 <del>.</del>	<del></del>	2x2	16M x 23x23N	MP	4	1122880	2320	3x3	16M x 22x22N	С	5
1644800	4112	4x4	16M x 20x20N	C	5	7 <u></u>	—	2x2	16M x 11x11N	MP	6
a		2x2	16M x 10x10N	MP	6	104000	1040	2x2	16M x 10x10N	С	7
148480	2320	3x3	16M x 8x8N	С	7	1 <u> 1</u>		2x2	16M x 5x5N	MP	8
		2x2	16M x 4x4N	MP	8	16640	1040	2x2	16M x 4x4N	C	9
25700	25700	1x1	100N	FC	9		_	2x2	16M x 2x2N	MP	10
202	202	1x1	2N	FC	10	6500	6500	1x1	100N	FC	11
					-	202	202	1x1	2N	FC	12

### **Performance results on the evaluation dataset**

DNN



method	precision recall $F_1$ score	method	precision recall $F_1$ score
DNN	0.88 0.70 <b>0.782</b>	NUS	0.63 0.40 0.490
DNNf12	0.85 0.68 0.758	ISIK [19]	0.28 0.68 0.397
DNNf1	0.78 0.72 0.751	ETH-HEILDERBERG [18	[] 0.14 0.80 0.374



#### Conclusions

- Our approach outperforms competing techniques by a large margin
- A general technique for bio-medical image segmentation (also used for EM segmentation – see NIPS 2012)
- Won four other competitions:
  - MICCAI 2013: Assessment of Mitosis Detection Algorithms
  - ISBI 2012: Neuronal Membrane Segmentation from Electron Microscopy images
  - ICDAR 2011: Offline Chinese Character Recognition
  - IJCNN 2011: The German Traffic Sign Recognition Benchmark

#### Future work

- Applying the method to other bio-medical problems
- Validating our approach on larger datasets, and comparing its performance to the one of expert histologists (already done successfully on the MICCAI Mitosis Detection Challenge)
- Bring automated mitosis detection into clinical practice

**More info** http://www.idsia.ch/~ciresan



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