Fast Mitosis Detection in Histopathological Images using Deep Learning Neural Networks



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Histopathological Image Analysis – Breast Cancer Diagnosis



Tissue Slide Staining

Image Scanning

Histopathological Image Analysis

Histopathological Image Analysis

Whole Slide Scale x10 Scale x40



Terminology:

Histopathological Images **Tissue Staining** Whole Image Slides Region of Tumor Region of Interest Cell

Mitosis



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Objectives: Counting Mitosis



Objective

Challenges in Mitosis Detection:

- Small objects with a large variety of shape configurations & texture variation
- Low frequency of appearance.
- Similarity with other types of nuclei







(a) Apoptosis

(b) Apoptosis

(c) Dust

MITOS dataset – ICPR 2012 Mitosis Detection Challenge

General Information

- 50 high-power fields (x40 magnitude) images in 5 different biopsy slides stained with Hematosin.
- Each field has 2048*2048 pixels representing a 512×512µm2 area.
- Expert pathologists manually annotated 300 mitoses. Average Mitosis size 30*30 pixels. Every pixel of each mitosis is labeled.
- The annotated mitoses are what two pathologists agreed on. So there are mitosis-like regions unannotated in these images.

Training Set

- 35 images (7 images from each biopsy slides)
- 200 mitoses annotated

Testing Set

- 15 images (3 images from each biopsy slides)
- 100 mitoses annotated

Structure of Convolutional Neural Network



12-layer CNN Model

Layer	Туре	Neurons	Filter Size
0	line	214 - 101 - 101	
U	input	31VI X 101 X 101	
1	Conv	16M x 100 x 100	2 x 2
2	MaxPool	16M x 50 x 50	2 x 2
3	Conv	16M x 48 x 48	3 x 3
4	MaxPool	16M x 24 x 24	2 x 2
5	Conv	16M x 22 x 22	3 x 3
6	MaxPool	16M x 11 x 11	2 x 2
7	Conv	16M x 10 x 10	2 x 2
8	MaxPool	16M x 5 x 5	2 x 2
9	Conv	16M x 4 x 4	2 x 2
10	MaxPool	16M x 2 x 2	2 x 2
11	FullyConn	100	1 x 1
12	FullyConn	2	1 x 1

Testing method: Sliding Window



Original Image

Convolutional Neural Network

Training of Convolutional Neural Network

Objective:

Create an image patch classifier react positively when mitosis is found in the center of a patch.

Challenges:

- Very few positive samples exist in the images. Only 200 Mitosis in training set. All the rest of the areas are nonmitosis
- Trained classifier needs to be rotational and shift invariant.

Solutions:

- We used random rotation, shift and mirroring to augmented the positive training samples.
- In the first stage, we are using 66000 mitosis and 66000 non-mitosis patches in training samples.
- Non-mitosis samples are randomly selected from the nonmitosis areas.

Augmented Training Samples:

training



testing



Training technique: Semi-supervised Learning



Step 1: Initial training set

- 66000 Mitosis
- 66000 Non-mitosis
- Positive Samples ---- Apply rotations and shifts on 200 mitosis.
- Negative Samples ---- Randomly sampled from the non-mitosis pixels.

Sampling Probability Map

Have the classifier learn difficult samples.

Step 2: Augmented training set

- 66000 Mitosis
- 1million Non-mitosis
- Positive Samples ---- Same samples as above
- Negative Samples ----Use the probability of false positive samples from last step as sampling probabilities to create a lot more difficult samples.

Testing Process



Accuracy from CNN Model with/ without 8 direction Average

	Precision	Recall	F-Score
Single Direction	0.78	0.74	0.758
8-direction Average	0.78	0.79	0.784
Original Paper	0.88	0.70	0.782

Accuracy from CNN Model with different thresholds

Threshold Values	Precision	Recall	F-Score
0.5	0.6905	0.8614	0.7665
0.6	0.7339	0.8345	0.7723
0.7	0.7767	0.7921	0.7843
0.8	0.8409	0.7327	0.7831
0.9	0.8659	0.7030	0.7760

		10-	layer DN	IN	1	2-layer DI	NN
CNN Classifier Accuracy		Prec	Recall	F-meas	Prec	Recall	F-meas
	Original Paper	0.78	0.72	0.751	0.88	0.70	0.782
	Scanning window + Initial Samples	0.74	0.13	0.221	0.93	0.04	0.084
	Scanning window + Augmented Samples	0.80	0.74	0.769	0.78	0.79	0.784
	Extracted DNN feat. + RF classifier	0.79	0.76	0.775	0.84	0.73	0.781
	Merged block-wise DNN feat. + RF classifier	Precision:	0.82	Recall:	0.76	F-meas:	0.789
0.849 0.844 0.842 0.841 0.828 0.824 0.820 0.802 0.786 0.785 TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE	0.784 0.781 0.773 0.773 0.771 0.767 TRUE TRUE TRUE TRUE TRUE TRUE	0.767 0.765 0. TRUE TRUE T	763 0.759 RUE FALSE	0.756 0.752 0 FALSE TRUE	0.746 0.741 TRUE TRUE	0.735 0.733 TRUE TRUE	0.712 0.696 0.6 TRUE TRUE TRUE
0.685 0.666 0.661 0.659 0.658 0.652 0.649 0.649 0.647 0.630 TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRU	0.622 0.607 0.603 0.601 0.589 0.584 TRUE TRUE TRUE TRUE TRUE TRUE	0.574 0.549 0. TRUE TRUE T	542 0.536 RUE TRUE	0.532 0.530 0 TRUE TRUE	0.524 0.517 TRUE FALSE	0.510 0.495 0 TRUE TRUE	0.491 0.473 0.4 TRUE TRUE TRU
0.463 0.461 0.457 0.440 0.433 0.428 0.421 0.415 0.410 0.408 TRUE TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRU	0.405 0.376 0.376 0.372 0.372 0.354 TRUE FALSE TRUE TRUE FALSE TRUE	0.350 TRUE TRUE T	339 0.339 RUE FALSE	0.336 0.334 0 TRUE FALSE F	0.328 0.319 ALSE TRUE	0.319 0.312 FALSE FALSE	0.312 0.309 0.3 FALSE FALSE TR
0.308 0.307 0.303 0.297 0.288 0.284 0.282 0.282 0.271 0.259 FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE TRUE TRUE FALSE	0.259 0.258 0.256 0.254 0.239 0.234 TRUE TRUE FALSE FALSE FALSE FALSE	0.234 0.234 0. FALSE TRUE FA	221 0.197 ALSE FALSE	0.194 0.194 (FALSE FALSE)	0.190 0.186 FALSE FALSE	0.186 0.185 FALSE FALSE	0.184 0.183 0.1 FALSE FALSE FAL
0.178 0.176 0.176 0.162 0.158 0.156 0.152 0.152 0.143 0.141 TRUE FALSE F	0.132 FALSE TRUE FALSE FALSE FALSE FALSE	0.121 0.120 0. FALSE FALSE F	120 0.114 ALSE FALSE	0.113 0.112 0 FALSE FALSE F	0.112 0.110 FALSE FALSE	0.110 0.106 (TRUE FALSE (•image •score •mitosis/n

CONVOLUCIONAL INCUTAL INCLINOIN

Training Efficiency

Convolutional Neural Network (Caffe library)

	ICPR Initial Set	ICPR Augmented Set	
	NVIDIA K40	NVIDIA K40	CPU
10-layer CNN	40 min.	8 hrs.	20hrs
12-layer CNN	2 hrs.	12 hrs.	45hrs

CNN-feature-based Method

Random forest classifier is trained in less than 1 minute with extracted features on a CPU machine.

Testing Efficiency

Convolutional Neural Network (5-pixel scanning interval)

Image tested with 8 rotations: 24min per image with CPU

Lots of unnecessary scans!!!



Accuracy & Efficien

Region-based Convolutional Neural Network



Input image Extract region proposals (~2k / image) e.g., selective search [van de Sande, Uijlings et al.]

Compute CNN features on regions Classify and refine regions

Region-based convolutional network

Initial Mitotic Region Proposal Generation



Mitosis Candidates

List of features (10 dimensions)

- Multiscale Gaussian Smoothing
- Multiscale Laplacian of Gaussian
- Difference of Gaussians
- Structure Tensor Eigenvalues
- Hessian of Gaussian Eigenvalues

Idea: Only Scan in proposed regions

Speed (2000 * 2000 pixel RGB image):

Proposal Generation – 10sec/per image

CNN classification in 8 directions – 20sec/per image with cpu.

Calls CNN function 3200 times /per image instead of 320,000 times / per image

Final RCNN-Based Mitosis Detection Pipeline



Stage 1: The CCE extracts pixelwise features at different scales and classifies each pixel as possibly mitosis or not

Stage 3: The FMP uses the same CNN to check multiple pixels and also multiple rotations.



Coarse Candidate Extractor

- 37 multi-scale features
 - Color (pixel values in Gaussian-smoothed color images)
 - Edge (Gaussian Gradient Magnitude, Gaussian Gradient Magnitude, Laplacian of Gaussian and Difference of Gaussian)
 - Texture (Structure Tensor Eigenvalues and Hessian of Gaussian Eigenvalues)
- Feature selection to reduce 37 to 10.
- Random forest classifier with six trees uses the 10 features to label pixels as mitotic candidate or not.

Fine Candidate Extractor

- Uses a CNN model trained using the ground truth training data provided by the organizers of the ICPR12 and ICPR 14 contests.
- We color normalized it according to a color transfer method described in Reinhard et al. 2001.
- Each pixel of each training image is labeled a mitosis if it is a pixel of a mitotic region and within 8 μm of the centroid.
- For ICPR14 data, which is probabilistic, only mitotic regions with probability > 0.6 were used.
- The two stage sampling techniques from Ciresan et al 2013 were used to build the final training image sample set.

Table 2: Architecture of our 5-layer CNN Classifier Model for Color-normalized patches.

Туре	Neurons	Filter Size
Input	$3 \times 101 \times 101$	
Conv	$16 \times 100 \times 100$	2×2
Relu	$16 \times 100 \times 100$	
MaxPool	$16 \times 50 \times 50$	2×2
Conv	$16 \times 48 \times 48$	3×3
Relu	$16 \times 48 \times 48$	
MaxPool	$16 \times 24 \times 24$	2×2
Conv	$16 \times 22 \times 22$	3×3
Relu	$16 \times 22 \times 22$	
MaxPool	$16 \times 11 \times 11$	2×2
Conv	$16 \times 10 \times 10$	2×2
Relu	$16 \times 10 \times 10$	
MaxPool	$16 \times 5 \times 5$	2×2
Conv	$16 \times 4 \times 4$	2×2
Relu	$16 \times 4 \times 4$	
MaxPool	$16 \times 2 \times 2$	2×2
FullyConn	100	
FullyConn	2	

Final Mitosis Predictor

- Inputs the binary image produced by the FCE and uses the same trained CNN, but in a sequence of scans of multiple different pixels of the input image.
- Each pixel that passes Stage 2 leads to a detailed search of a region around it for evidence of a mitotic figure.
- A spiral scan path carries out this detailed search.
- Pixels that pass Stage 2 become the centers for the first scan in Stage 3 at an intermediate threshold.
- If a pixel in the first scan passes, the system goes into a finer scanning mode at a final threshold.

Scan path of final mitosis classifier



Results on ICPR 2012 and 2014 Datasets

Table 3: Preliminary Results on ICPR 2014 test datasets

		Chen & Hao	Ours
	Precision	0.80	0.78
ICPR12	Recall	0.77	0.79
	F-Measure	0.788	0.784
	Precision	not rep.	0.654
ICPR14	Recall	not rep.	0.663
in group	F-Measure	not rep.	0.659
	Precision	0.46	0.40
ICPR14	Recall	0.51	0.45
out group	F-measure	0.482	0.427

	Chen & Hao	Ours
CNN calls	2961	1743
GPU inference time	4.62s	0.838
CPU inference time	408.91s	6.03s
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