# Deep-learning And Digital Pathology

G. Thomas Brown, MD, PhD Artificial Intelligence Resource, NCI NCI/NIH 06/15/2021

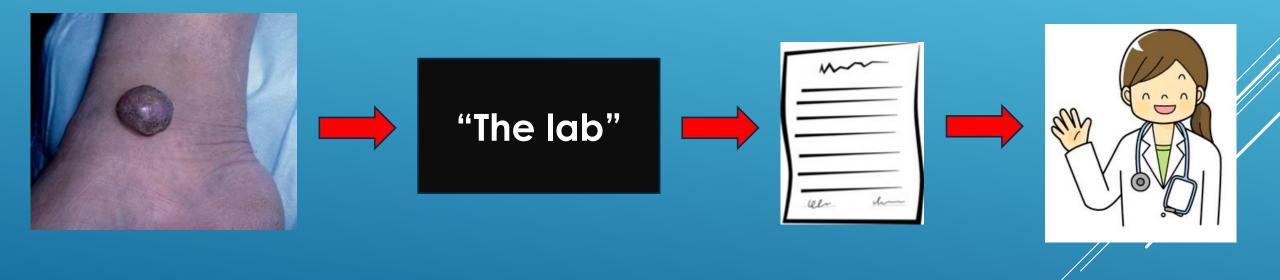


- Introduction to Pathology
- Introduction to Digital Pathology
- Interesting publications
- Combining machine learning with pathology

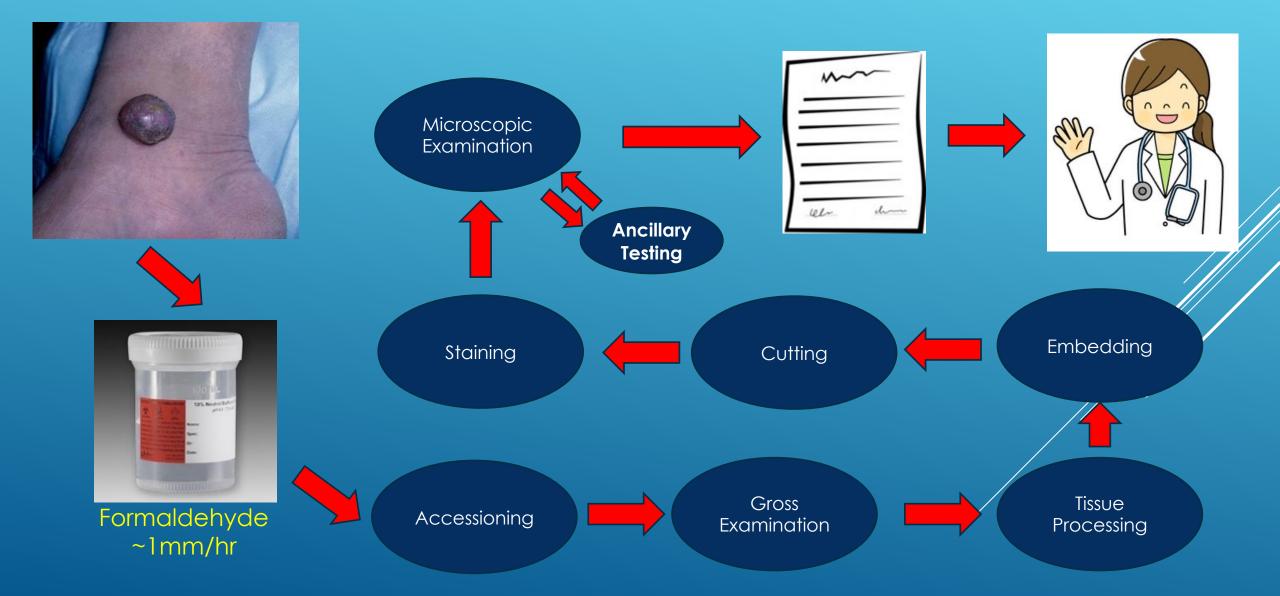




### INTRODUCTION TO PATHOLOGY



### SURGICAL PATHOLOGY WORKFLOW



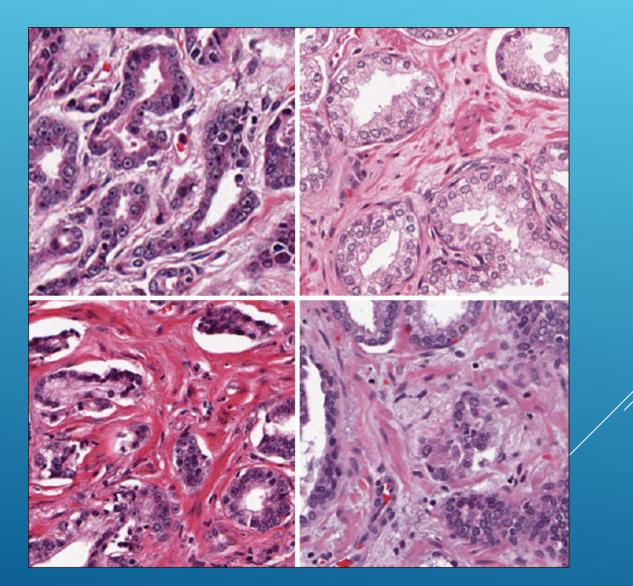
# TISSUE STAINING

- ► Hematoxylin & Eosin
- Mounting media
- ► Coverslip



Prostate Sof Cancer

### COLOR VARIATION



#### DIGITAL PATHOLOGY



Review finds more cases handled by impaired pathologist at VA clinic in Fayetteville, Ark.



Posted: Tue 1:53 PM, Jan 29, 2019



**FAYETTEVILLE, Ark. (AP)** – A pathologist accused of working while impaired at a Fayettevile, Ark. Veterans Affairs hospital handled 96 cases as a private consultant before he was hired, according to an independent review.

Dr. Robert Morris Levy has acknowledged that he once showed up to work at the Veterans Health Care System of the Ozarks drunk in 2016, but he denies working while impaired.

Kelvin Parks, the system's director told veterans at a town hall meeting on Monday that outside pathologists reviewed nearly 34,000 cases handled by Levy and found more than 3,000 errors or missed diagnoses, the Northwest Arkansas Democrat-Gazette reported. The cases date back to 2005.

Review finds more cases handled by impaired pathologist at VA clinic in Fayetteville, Ark.



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Review finds more cases handled by impaired pathologist at VA clinic in Fayetteville, Ark.

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		REPORT COVID-19 FRAUD Contact the National Center for			
FOR IMMEDIATE RELEASE			Friday, Janu	1ary 22, 2021	Disaster Fraud Hotline: 866-720-5721 or Justice.gov/DisasterComplaintForm
Fayetteville Doc For Mail 1	tor Sentenced To Fraud And Involu			Prison	
	cases as a private consultant peror		1		
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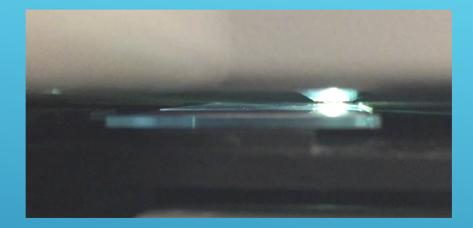
#### WHOLE-SLIDE IMAGING

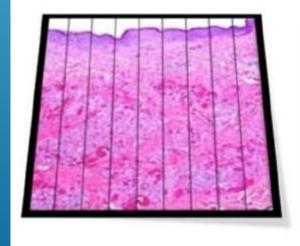


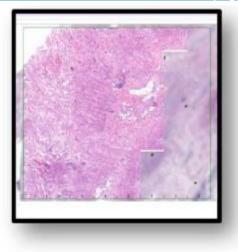
### WHOLE-SLIDE IMAGING (WSI)

- Image capture device
  - Motorized
- Microscope objective









### WSI FORMAT

- ► 20x or 40x magnification
  - ▶ 0.5 µm/pixel or 2.75 µm/pixel
- ► 1-5 minutes per glass slide

#### ► Large file sizes

- ► Gigapixel range, 0.5-2GB file sizes
- LZW/TIF or some lossless compression\*
- Image tiling and image pyramids



## OPENSLIDE

- ► Open source C library
  - ► Java, python
- ► API
  - ► OpenSeaDragon
- ► Reverse engineered
  - ► Aperio
  - ► Hamamatsu
  - ► Leica
  - ► Phillips
  - ▶ Sakura
  - ► Ventana
  - 3DHISTECH MRXS ("MIRAX")
  - And more

#### TECHNICAL NOTE

J Pathol Inform 2013, 4:27

#### OpenSlide: A vendor-neutral software foundation for digital pathology

#### Adam Goode<sup>1</sup>, Benjamin Gilbert<sup>2</sup>, Jan Harkes<sup>2</sup>, Drazen Jukic<sup>3</sup>, Mahadev Satyanarayanan<sup>2</sup>

<sup>1</sup> School of Computer Science, Carnegie Mellon University; Google, Pittsburgh, PA, USA

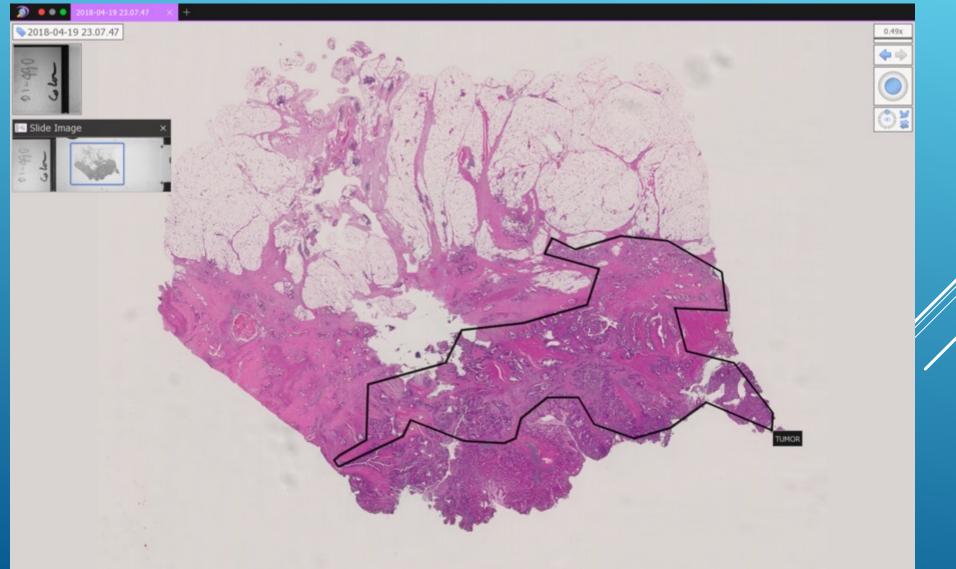
<sup>2</sup> School of Computer Science, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA

<sup>3</sup> Department of Pathology and Dermatology, University of Pittsburgh, Pittsburgh, Pennsylvania; James A. Haley Veterans Hospital and University of South Florida, Tampa, FL, USA

# **BENEFITS OF NIH**

- NCI / AIR Computer vision expertise
  - ▶ DGX-A100 (8x A100's; 320GB VRAM)
  - Pathologists, Radiologists, Data Scientists
- ► NCI
  - ► CBIIT
    - ► HALO, Palantir, etc
- NIH Clinical Center Rich source of medical samples
  - ► ~6-7k pathology cases per year
  - All cases research (IRB protocol)
- ► NIH-wide
  - ► Biowulf/Helix
    - ► Many V100's
    - Many A100's





# MACHINE LEARNING AND PATHOLOGY

# MACHINE LEARNING AND PATHOLOGY

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Research ARTICLE
Pigeons (*Columba livia*) as Trainable Observers of Pathology
and Radiology Breast Cancer Images

Richard M. Levenson 🖾, Elizabeth A. Krupinski, Victor M. Navarro, Edward A. Wasserman 🖾

Published: November 18, 2015 • https://doi.org/10.1371/journal.pone.0141357

# MACHINE LEARNING AND PATHOLOGY

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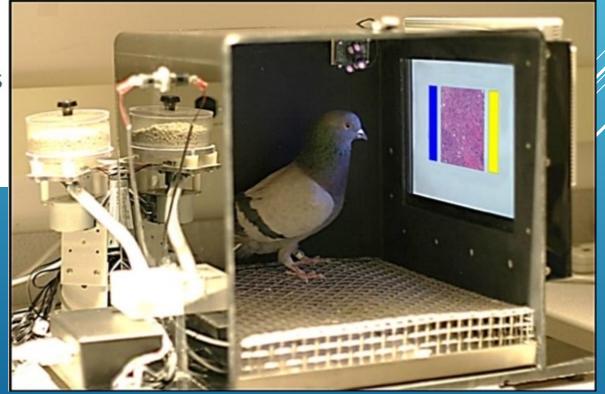
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RESEARCH ARTICLE

#### Pigeons (*Columba livia*) as Trainable Observers and Radiology Breast Cancer Images

Richard M. Levenson D, Elizabeth A. Krupinski, Victor M. Navarro, Edward A. Wasserman D

Published: November 18, 2015 • https://doi.org/10.1371/journal.pone.0141357



#### NO NEED FOR PATHOLOGIST ROI'S?

#### nature medicine

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#### Article | Published: 15 July 2019

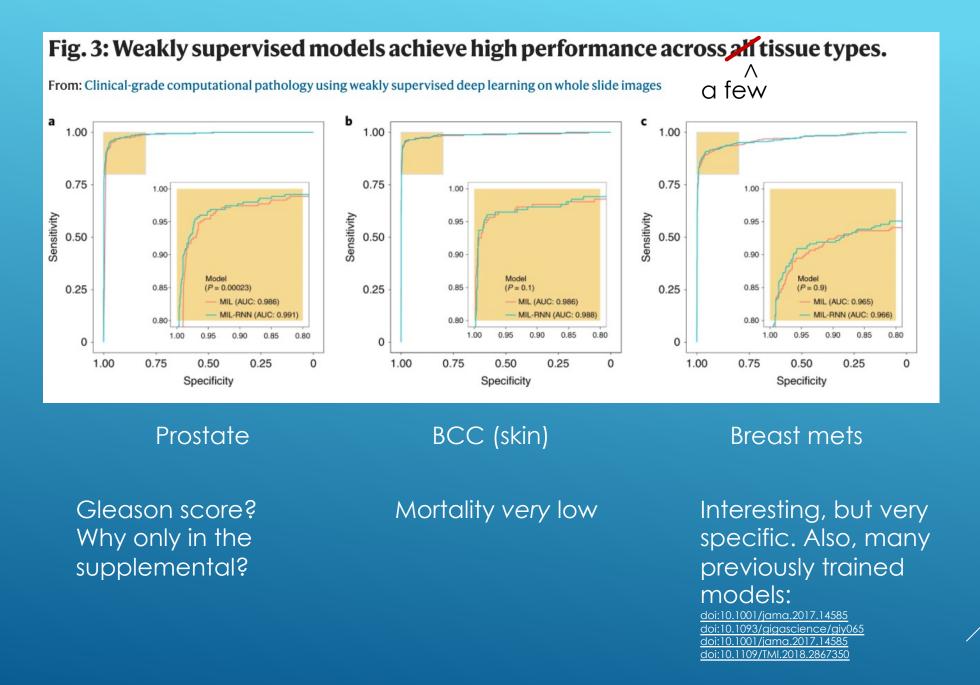
#### Clinical-grade computational pathology using weakly supervised deep learning on whole slide images

Gabriele Campanella, Matthew G. Hanna, Luke Geneslaw, Allen Miraflor, Vitor Werneck Krauss Silva, Klaus J. Busam, Edi Brogi, Victor E. Reuter, David S. Klimstra & Thomas J. Fuchs 🖂

Nature Medicine 25, 1301–1309 (2019) | Cite this article 38k Accesses | 273 Citations | 547 Altmetric | Metrics

#### Abstract

The development of decision support systems for pathology and their deployment in clinical practice have been hindered by the need for large manually annotated datasets. To overcome this problem, we present a multiple instance learning-based deep learning system that uses only the reported diagnoses as labels for training, thereby avoiding expensive and time-consuming pixel-wise manual annotations. We evaluated this framework at scale on a dataset of 44,732 whole slide images from 15,187 patients without any form of data curation. Tests on prostate cancer, basal cell carcinoma and breast cancer metastases to axillary lymph nodes resulted in areas under the curve above 0.98 for all cancer types. Its clinical application would allow pathologists to exclude 65–75% of slides while retaining 100% sensitivity. Our results show that this system has the ability to train accurate classification models at unprecedented scale, laying the foundation for the deployment of computational decision support systems in clinical practice.



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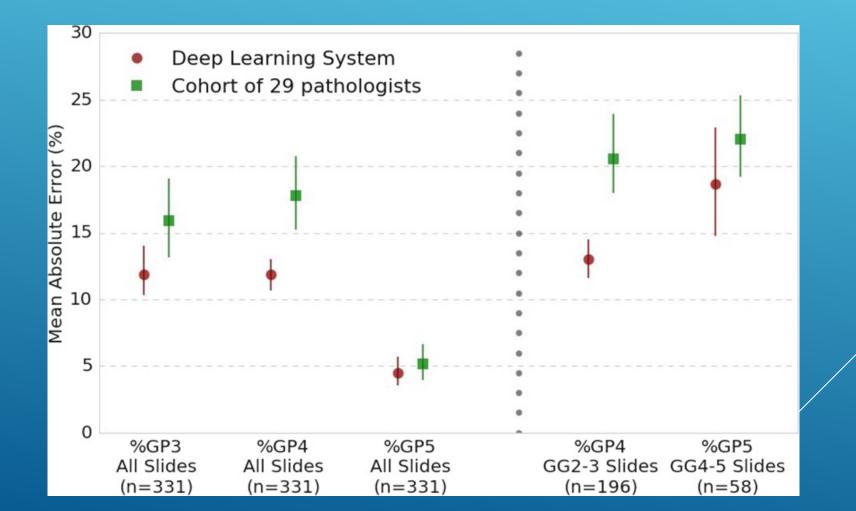
Article Open Access Published: 07 June 2019

# Development and validation of a deep learning algorithm for improving Gleason scoring of prostate cancer

Kunal Nagpal, Davis Foote, Yun Liu, Po-Hsuan Cameron Chen, Ellery Wulczyn, Fraser Tan, Niels Olson, Jenny L. Smith, Arash Mohtashamian, James H. Wren, Greg S. Corrado, Robert MacDonald, Lily H. Peng, Mahul B. Amin, Andrew J. Evans, Ankur R. Sangoi, Craig H. Mermel ⊠, Jason D. Hipp & Martin C. Stumpe ⊠

npj Digital Medicine 2, Article number: 48 (2019) | Cite this article 16k Accesses | 87 Citations | 238 Altmetric | Metrics

### HUMAN COMPARISON



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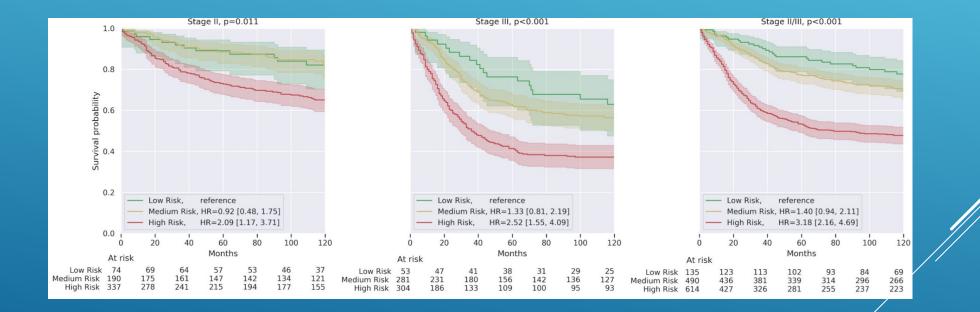
Article Open Access Published: 19 April 2021

# Interpretable survival prediction for colorectal cancer using deep learning

Ellery Wulczyn, David F. Steiner, Melissa Moran, Markus Plass, Robert Reihs, Fraser Tan, Isabelle Flament-Auvigne, Trissia Brown, Peter Regitnig, Po-Hsuan Cameron Chen, Narayan Hegde, Apaar Sadhwani, Robert MacDonald, Benny Ayalew, Greg S. Corrado, Lily H. Peng, Daniel Tse, Heimo Müller, Zhaoyang Xu, Yun Liu , Martin C. Stumpe, Kurt Zatloukal & Craig H. Mermel

npj Digital Medicine 4, Article number: 71 (2021) Cite this article

### PREDICTING RISK!



#### nature medicine

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nature > nature medicine > articles > article

#### Article | Published: 17 September 2018

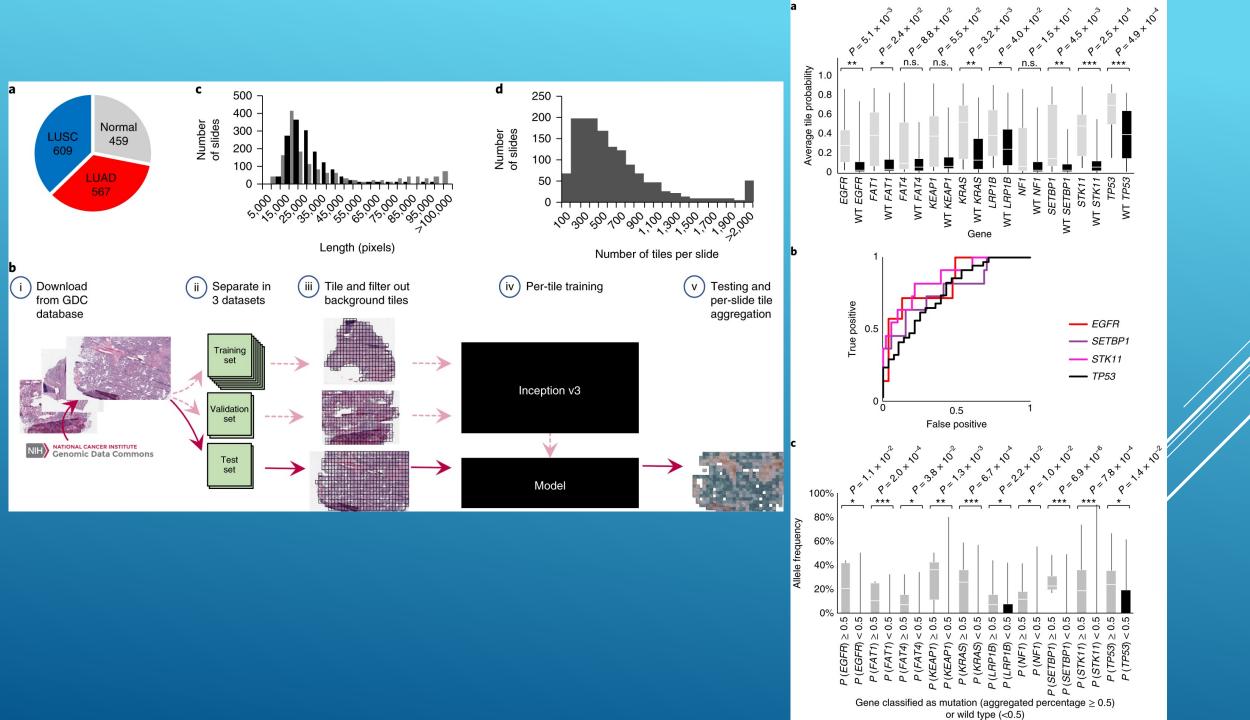
#### Classification and mutation prediction from nonsmall cell lung cancer histopathology images using deep learning

Nicolas Coudray, Paolo Santiago Ocampo, Theodore Sakellaropoulos, Navneet Narula, Matija Snuderl, David Fenyö, Andre L. Moreira, Narges Razavian ⊠ & Aristotelis Tsirigos ⊠

Nature Medicine 24, 1559–1567 (2018) | Cite this article 53k Accesses | 534 Citations | 1113 Altmetric | Metrics

#### Abstract

Visual inspection of histopathology slides is one of the main methods used by pathologists to assess the stage, type and subtype of lung tumors. Adenocarcinoma (LUAD) and squamous cell carcinoma (LUSC) are the most prevalent subtypes of lung cancer, and their distinction requires visual inspection by an experienced pathologist. In this study, we trained a deep convolutional neural network (inception v3) on whole-slide images obtained from The Cancer Genome Atlas to accurately and automatically classify them into LUAD, LUSC or normal lung tissue. The performance of our method is comparable to that of pathologists, with an average area under the curve (AUC) of 0.97. Our model was validated on independent datasets of frozen tissues, formalin-fixed paraffin-embedded tissues and biopsies. Furthermore, we trained the network to predict the ten most commonly mutated genes in LUAD. We found that six of them–STK11, EGFR, FAT1, SETBP1, KRAS and TP53–can be predicted from pathology images, with AUCs from 0.733 to 0.856 as measured on a heldout population. These findings suggest that deep-learning models can assist pathologists in the detection of cancer subtype or gene mutations. Our approach can be applied to any cancer type, and the code is available at https://github.com/ncoudray/DeepPATH.



#### INTRODUCTION

- Cervical Cancer
  - One of the most common cancer among women.
  - $\blacktriangleright$  2018 US Statistics  $\triangle$ 
    - ▶ 13,240 diagnosed cases.
    - ► 4,170 women die from cervical cancer.
  - Cervical cancer that is detected early is more likely to be treated successfully.

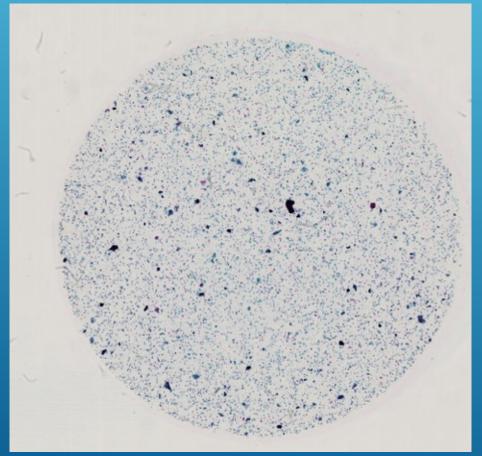


#### NLM Data

- ► 25 cytology slides.
  - Provided by BD (Becton-Dickinson) Corporation.
  - ► The slides are prepared using Sure Path.
- Herlev Pap Smear Dataset
  - ► 917 cervical cell images

### NLM DATA

#### Clean Slide image



#### Annotated Slide image



Note: Displayed images are from level 7

#### **ROI DETECTION**

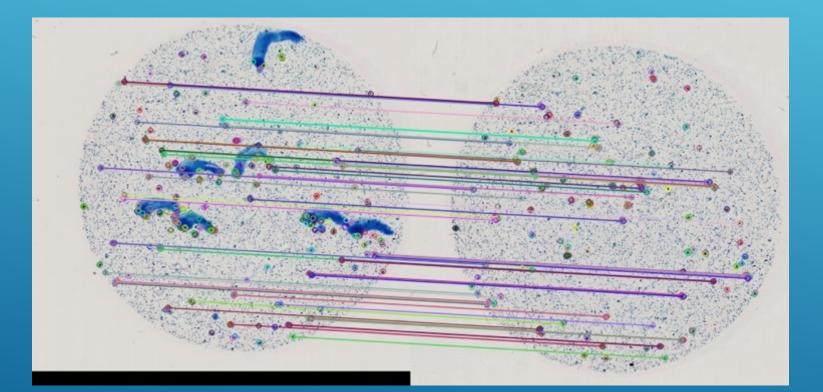


Image Registration
ORB feature detector <sup>A</sup>
Match features
Calculate Homography
Uses RANSAC\* estimation technique

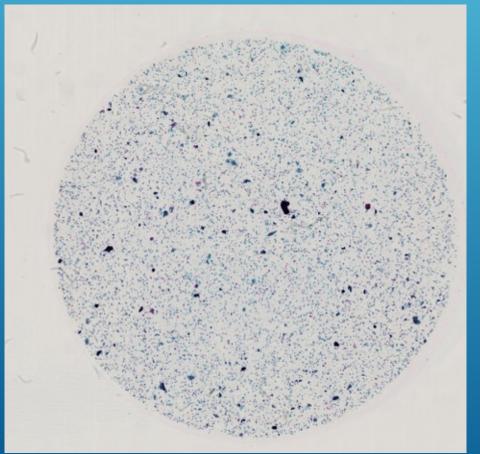
#### Matching Keypoints

<sup>a</sup> Ethan Rublee, Vincent Rabaud, Kurt Konolige, Gary R. Bradski: ORB: An efficient alternative to SIFT or SURF. ICCV 2011: 2564-2571

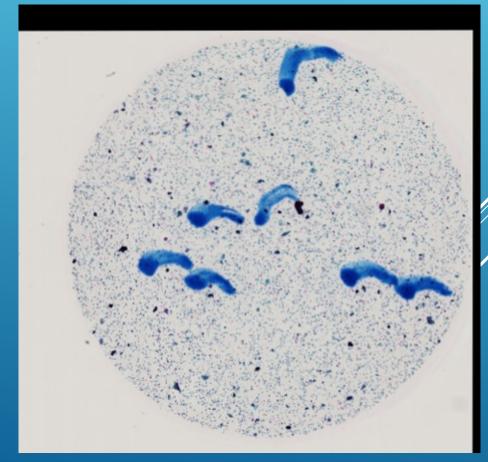
\* Random sample consensus (RANSAC) is an iterative method to estimate parameters of a mathematical model from a set of observed data that contains outliers

# ROI DETECTION Image Registration

Reference Image

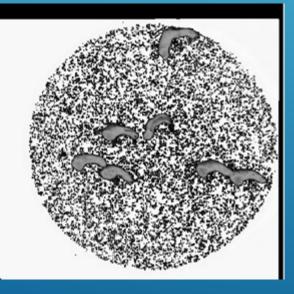


#### Aligned Image

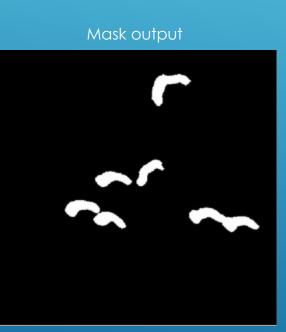


# **ROI DETECTION**



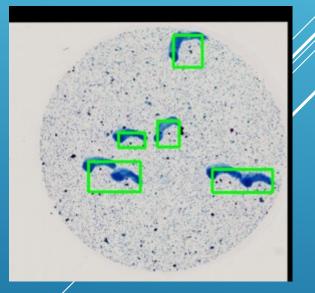


#### Threshold + Morphological operations

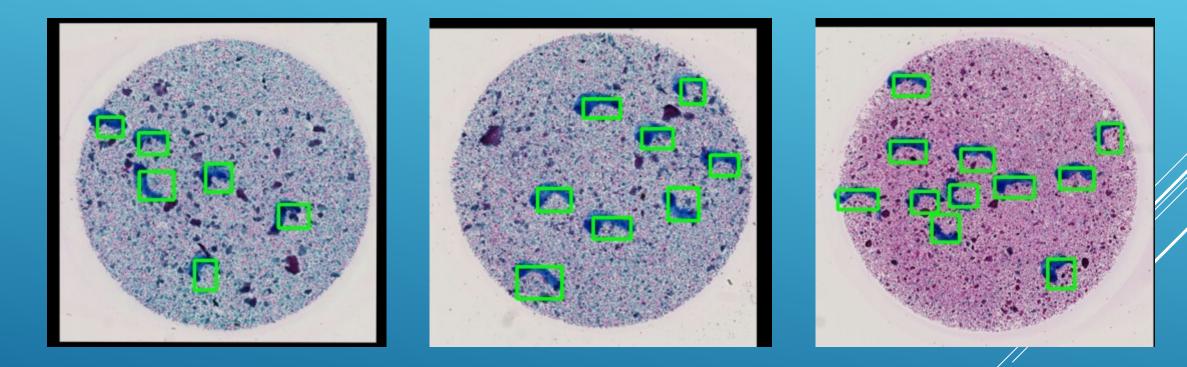


#### Skeletonize + Refine boundaries

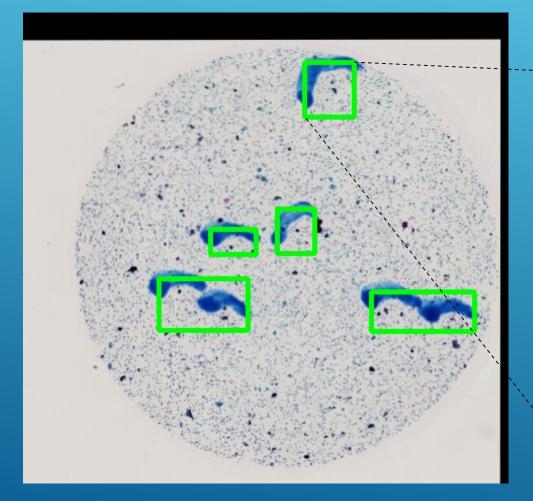
#### ROIs detected



# **ROI DETECTION RESULTS**



### LOCATING ABNORMAL CELLS



Size: 3400x3079

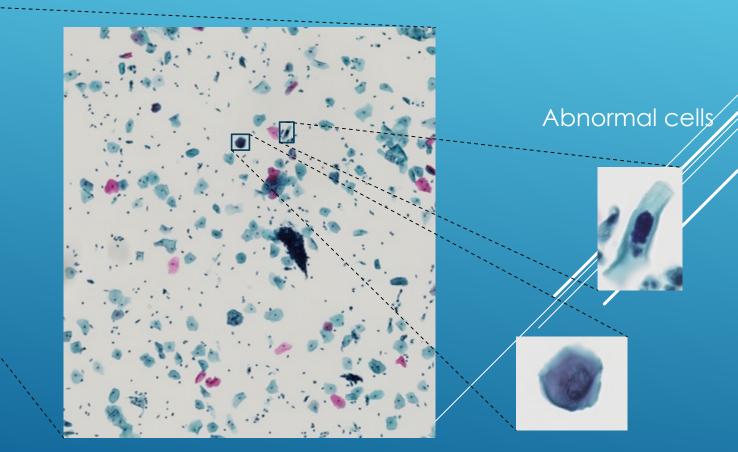


Image from level 7

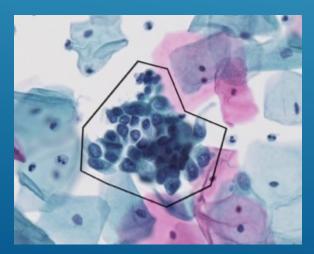
Image from level 1

### SLIDE CLASSIFICATION

 NILM (Negative for Intraepithelial Lesion or Malignancy)



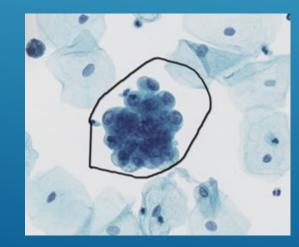
 HSIL (Higher-grade Squamous intraepithelial lesion)



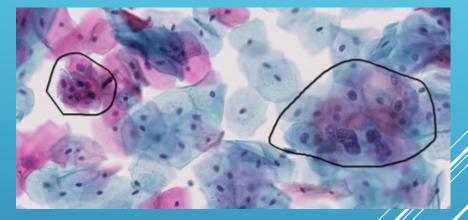
 ASCUS (Atypical squamous cells of undetermined significance)



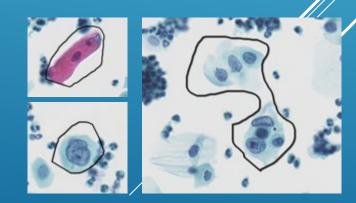
Adeno (Adenocarcinoma)



 LSIL (Lower-grade Squamous intraepithelial lesion)

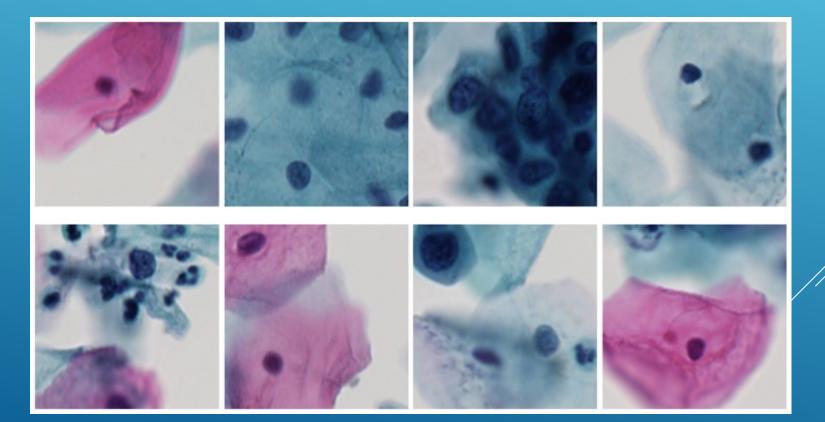


SCC (Squamous cell carcinoma)



### PATCH BASED DATA GENERATION

#### 128x128 patch images



Normal

Abnormal

### CLASSIFICATION

- ► This is a Bi-classfication
- ► Train, Test Dataset
  - Training Dataset (Herlev Pap Data)
    - Training: Normal 196, Abnormal 560
    - ► Validation: Normal 46, Abnormal 115
  - Testing Dataset (12X\$12118 Patch data)
    - ► Testing: 15,035 patch (128x128) images

#### CLASSIFICATION

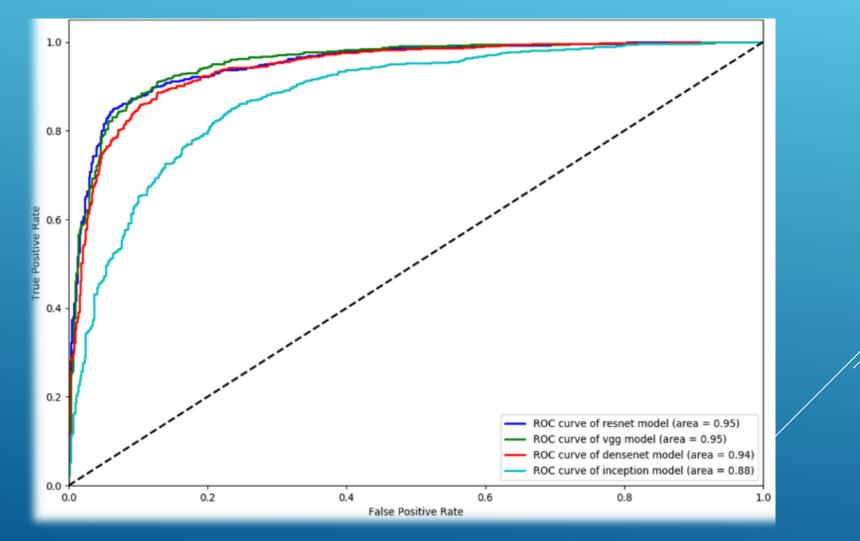
- CNN based Classifier
- ► Fine-tuning models initialized with pre-trained ImageNet weights.
- ► No. of Epochs = 200
- ► Batch Size = 32
- Optimizer: Stochastic Gradient Descent
  - ► Lr = 0.001, Momentum = 0.9
- Loss Function: Cross Entropy Loss

### CLASSIFICATION RESULTS

- Pytorch Deep Learning Platform.
- Models run on Nvidia DGX station.
- Evaluation results for normal class detection

Model	Confusion	ACC	PREC	REC	F1-	MCC
	$ \begin{array}{c} \text{matrix} \\ \begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix} \end{array} $				Score	
Resnet-50	$\begin{bmatrix} 589 & 71 \\ 78 & 582 \end{bmatrix}$	0.8871	0.8913	0.8818	0.8865	0.7742
VGG-19	$\begin{bmatrix} 581 & 79 \\ 68 & 592 \end{bmatrix}$	0.8886	0.8823	0.8970	0.8896	0.7773
Densenet- 121	$\begin{bmatrix} 611 & 49 \\ 131 & 529 \end{bmatrix}$	0.8636	0.9152	0.8015	0.8546	0.7329
Inception _v3	$\begin{bmatrix} 429 & 231 \\ 57 & 603 \end{bmatrix}$	0.7818	0.7230	0.9136	0.8072	0.5843

# CLASSIFIER COMPARISON



#### SUMMARY

- Digital pathology images are large
- Color variation, magnification should be considered
- Deep learning and pathology can assess diagnosis AND:
  - Assist with grading (Gleason, Elston, Weiss, etc)
  - Predict outcomes
  - Predict molecular mutations
- Collecting and curating dataset is extremely important
- Evaluate models thoroughly
- Different architectures can use more computer power, ie take longer to train

### RESOURCES

#### ► Courses:

- ► THIS lecture series!
- ► Fast AI : <u>https://course.fast.ai/</u>
- ► Coursera
- Khan Academy

#### Challenges:

- ► Grand-challenge.org
- Nuclear segmentation
- ► Tumor segmentation

## ACKNOWLEDGMENTS

#### ► NCI/AIR

- Stephanie Harmon, PhD
- ► Nathan Lay, PhD
- ► Baris Turkbey, MD
- ▶ Peter Choyke, MD
- ► Collaborators
  - ► Stephen Hewitt, MD, PHD
  - Sameer Antani, PHD
  - ▶ Paul Fontelo, MD, MPh
- ► Helpful people
  - Sudhir Sornapudi (Missouri S&T)

