

# AI Breakthrough in Computational Pathology

AN ENABLER IN PERSONALISED CANCER TREATMENT

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# Outline

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Introduction to Computational Pathology (CP)

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Whole Slide Images

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Application of AI in CP

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Importance of AI in CP

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AI based CP Workflow

---

Top Tier Publications

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Challenges

---

State CP in Pakistan

---

Two case studies

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Conclusion

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# Definitions

## Pathology

- The science of the causes and effects of diseases
- Especially, the branch of medicine that deals with the laboratory examination of samples of body tissue for diagnostic or forensic purposes

## Histopathology

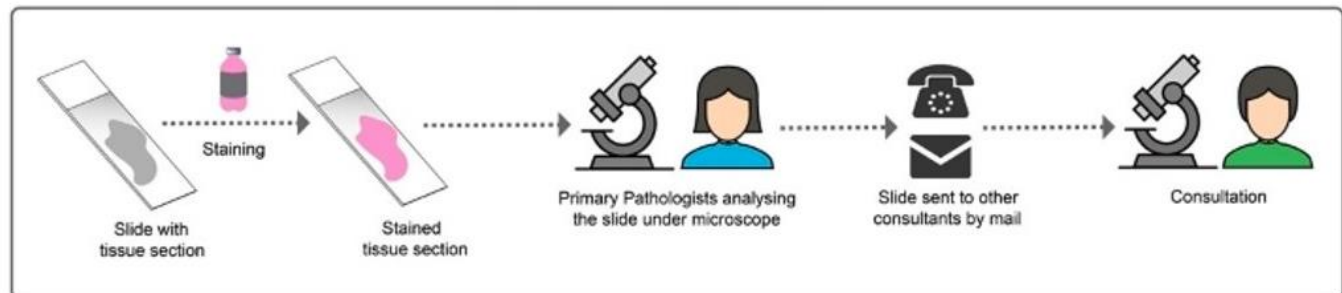
- Sub-branch of pathology
- It is concerned with the investigation of disease by examining cells and tissues

## Pathologist/Histopathologist

- A scientist/doctor who studies the causes and effects of diseases

## Glass Slides

- A glass slide is a thin, flat, rectangular piece of glass that is used as a platform for microscopic specimen observation.



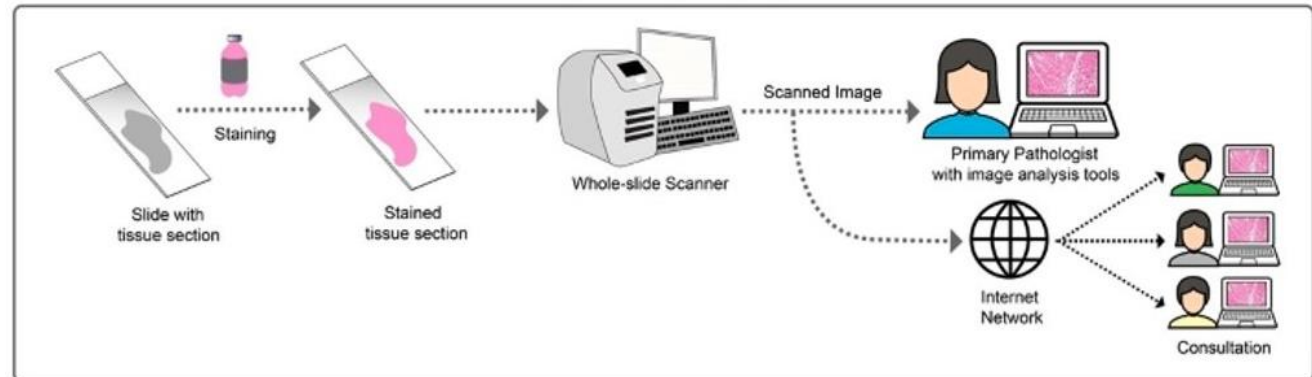
# Definitions

## Digital Pathology

- It incorporates the acquisition, management, sharing and interpretation of pathology information — including slides and data — in a digital environment.

## Digital Slides/ Whole Slides Images

- Whole slide imaging, also known as virtual microscopy, refers to scanning a complete glass slide and creating a single high-resolution digital file.



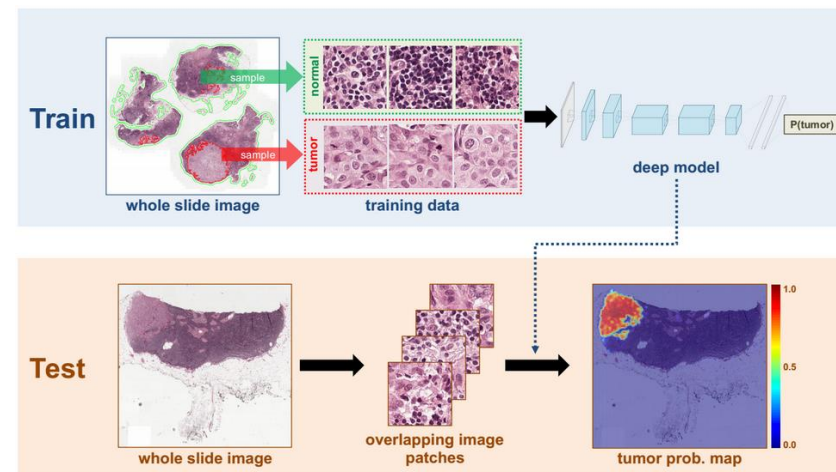
# Definitions

## Computational Pathology (CP)

- It is the analysis of digitized pathology images with associated metadata, typically using artificial intelligence (AI) methods.

## Deep learning is CP

- It is a type of AI method, commonly used in computational pathology, that is able to "learn" how to perform tasks based on examples.



# Motivation to work in Computational Pathology

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Computational Pathology is an applied field of Computer Vision/Artificial Intelligence

It is quite new as compared to other medical imaging based applied fields

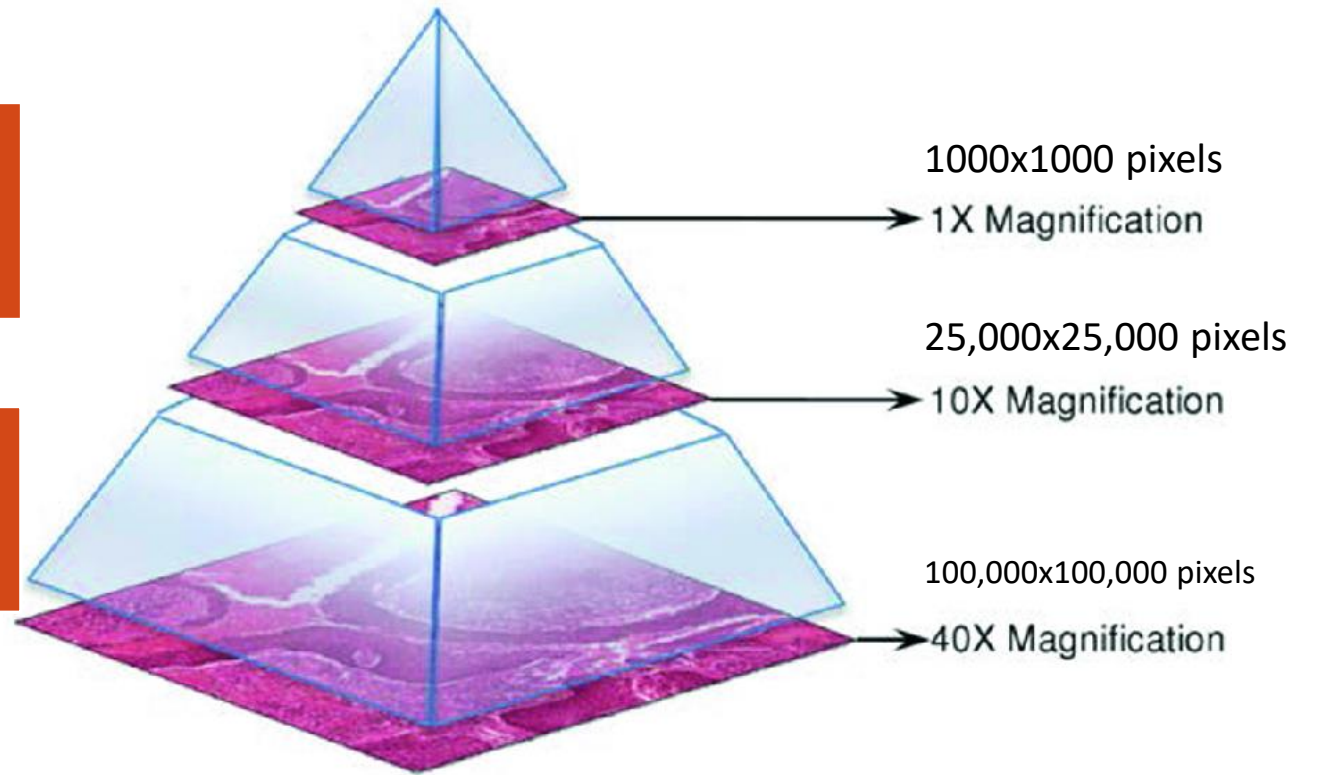
In this field competition is low therefore, probability to get a PhD position or Job in a top university/organization is high 😊

# Whole Slide Images

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Takes 1-4 GB of space on disk when save in compressed format

Don't try to load these images into memory at highest magnification



# Whole Slide Images

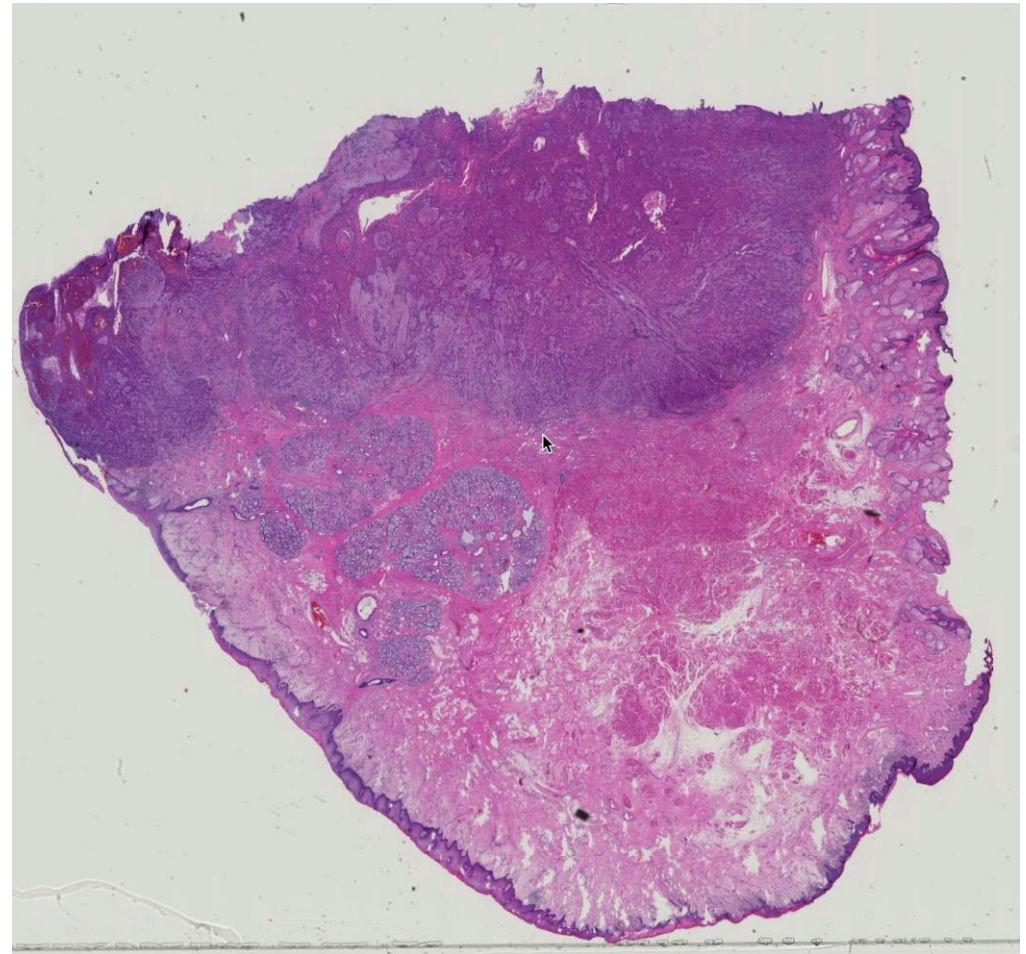
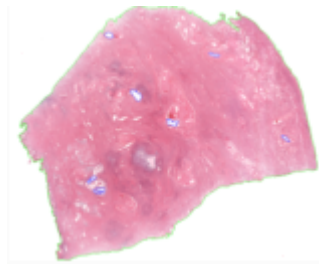
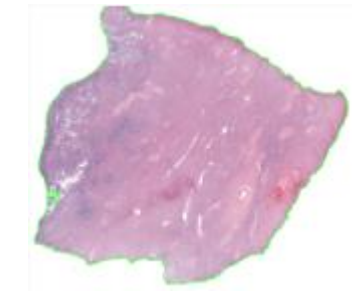
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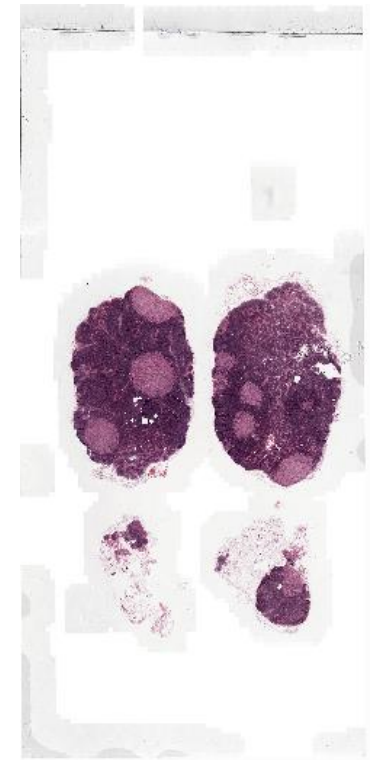
# Whole Slide Images

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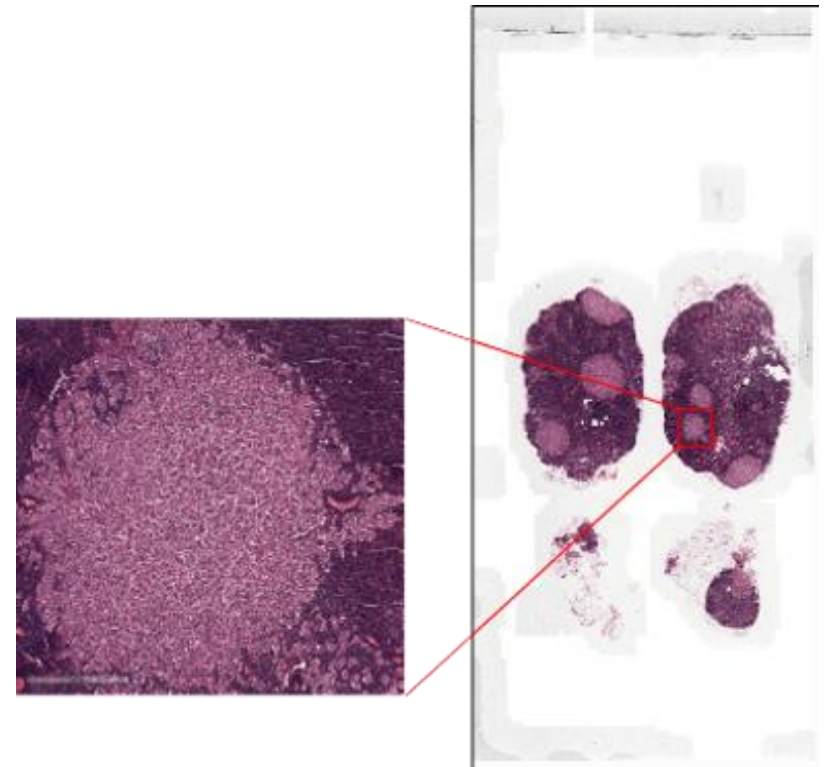
# Whole Slide Images

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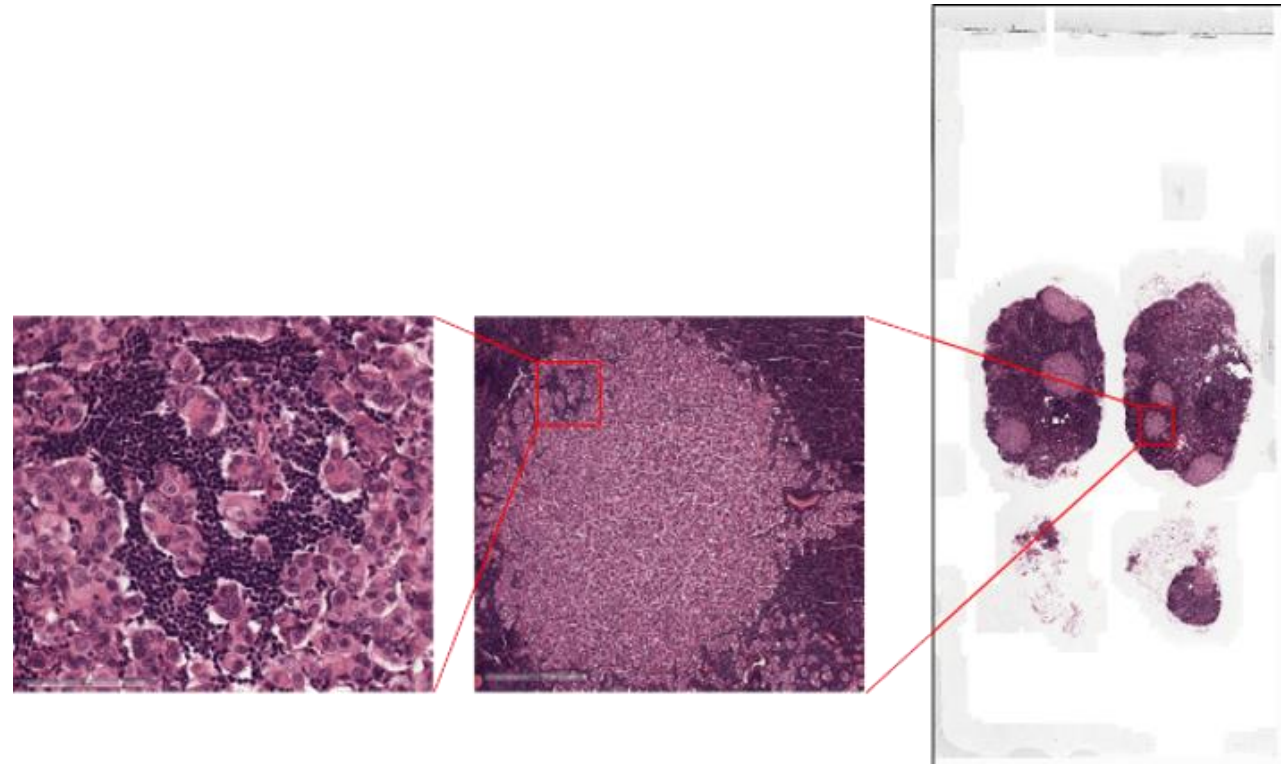
# Whole Slide Images

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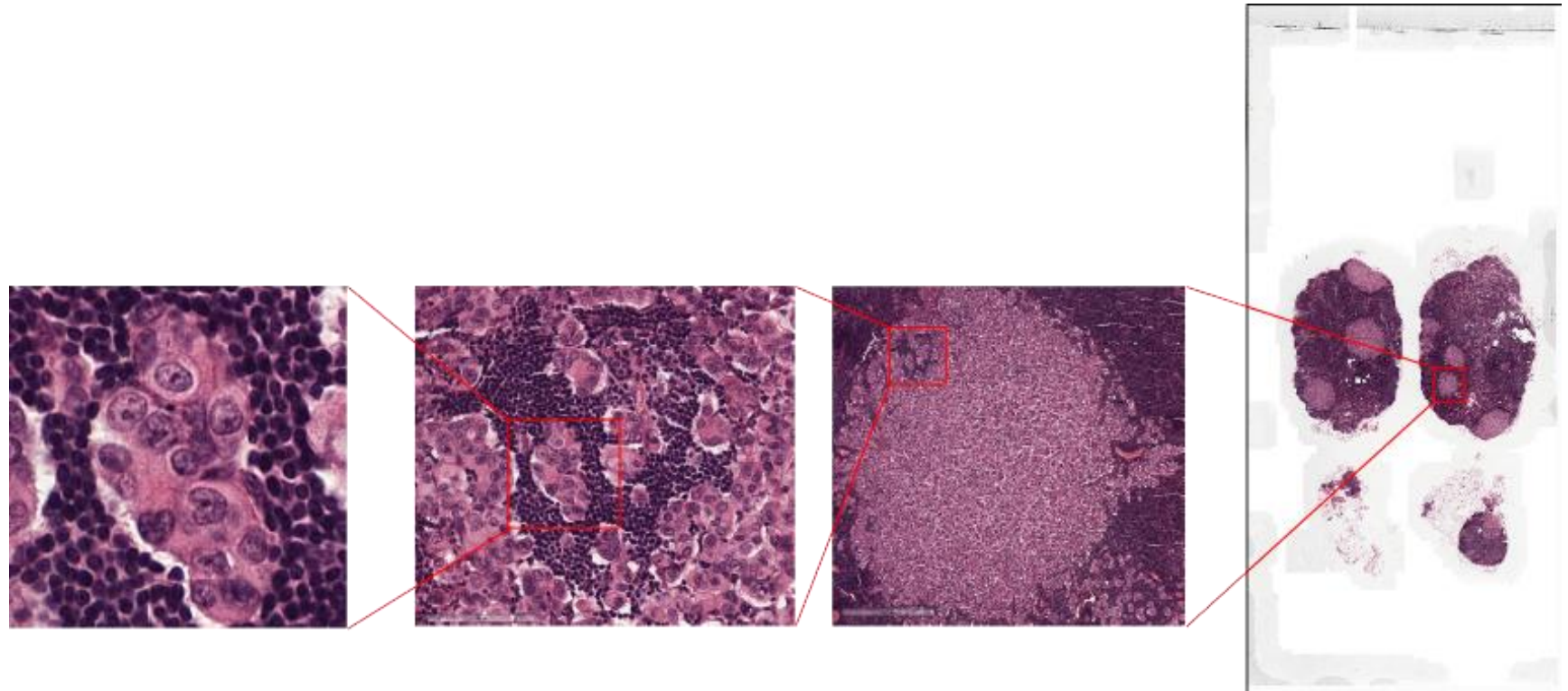
# Whole Slide Images

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# Whole Slide Images

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# Application of AI in CP

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## **Cancer Diagnosis/Detection**

- A pathologist looks at the tissue under a microscope to see if the tissue has tumor cells or regions

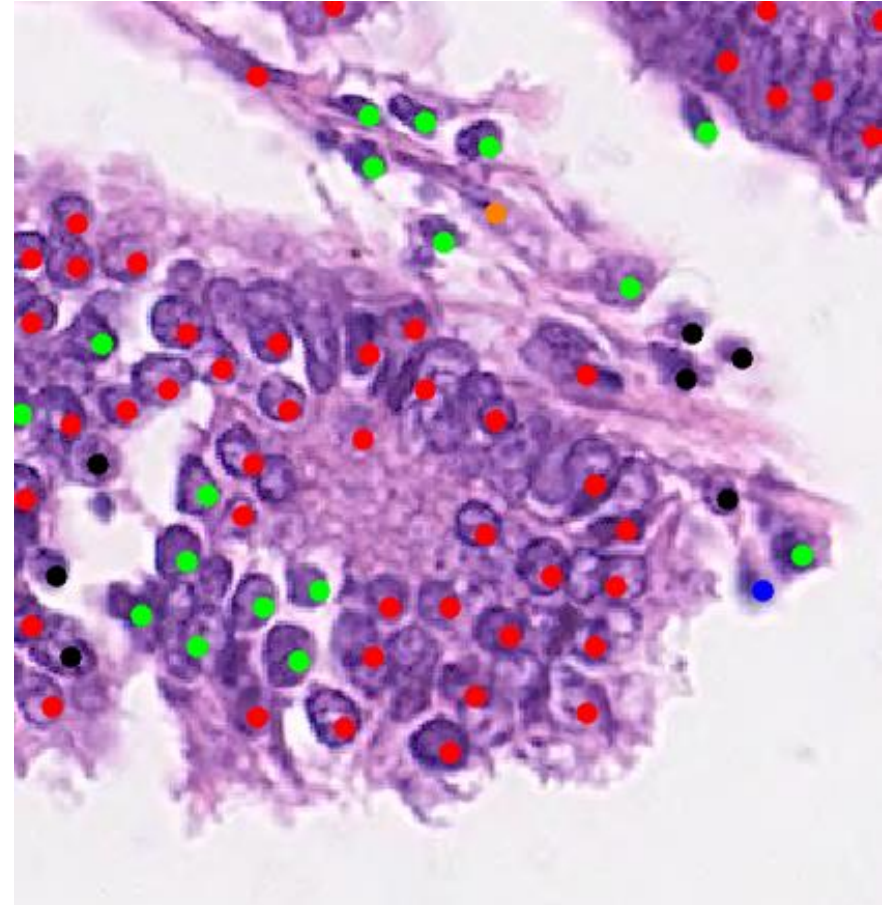


# Application of AI in CP

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## Cancer Diagnosis/Detection

- A pathologist looks at the tissue under a microscope to see if the tissue has tumor cells or regions
- Cancer Diagnosis is basically an **objection detection and classification problem** where object of interest are tumor cells and normal cells

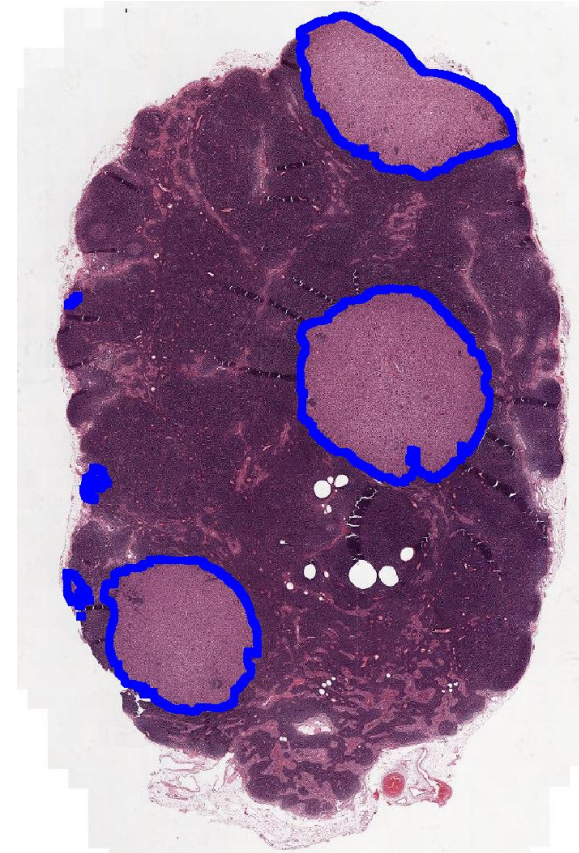


# Application of AI in CP

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## Cancer Diagnosis/Detection

- A pathologist looks at the tissue under a microscope to see if the tissue has tumor cells or regions
- Cancer Diagnosis is basically an **objection detection and classification problem** where object of interest are tumor cells and normal cells
- Cancer detection can be considered as **segmentation problem** at WSI level

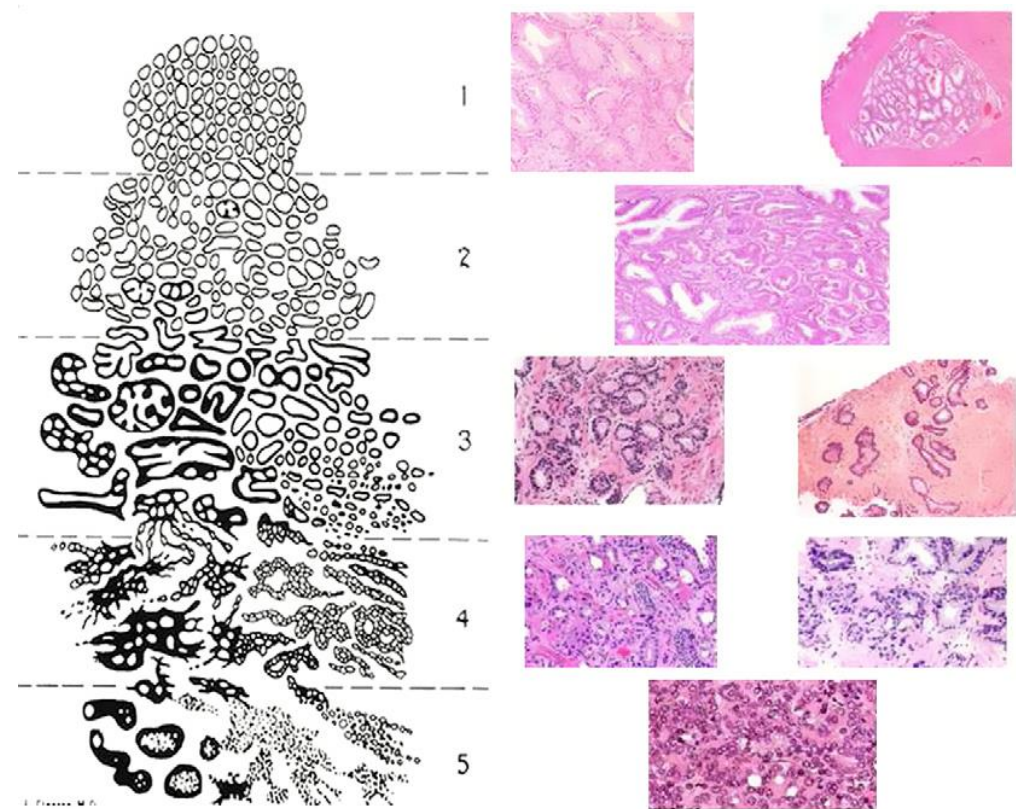




# Application of AI in CP

## Cancer Grading

- A pathologist looks at the tissue under a microscope and grade how different the cancer cells look compared to normal, healthy cells

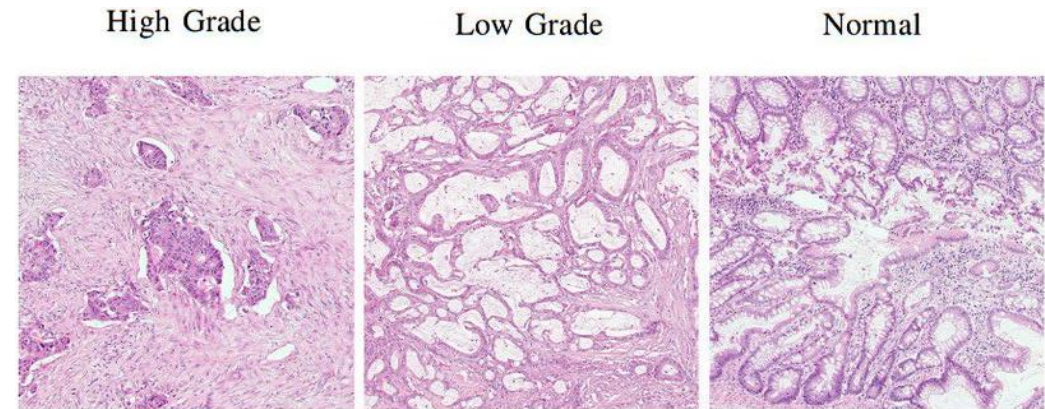


# Application of AI in CP

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## Cancer Grading

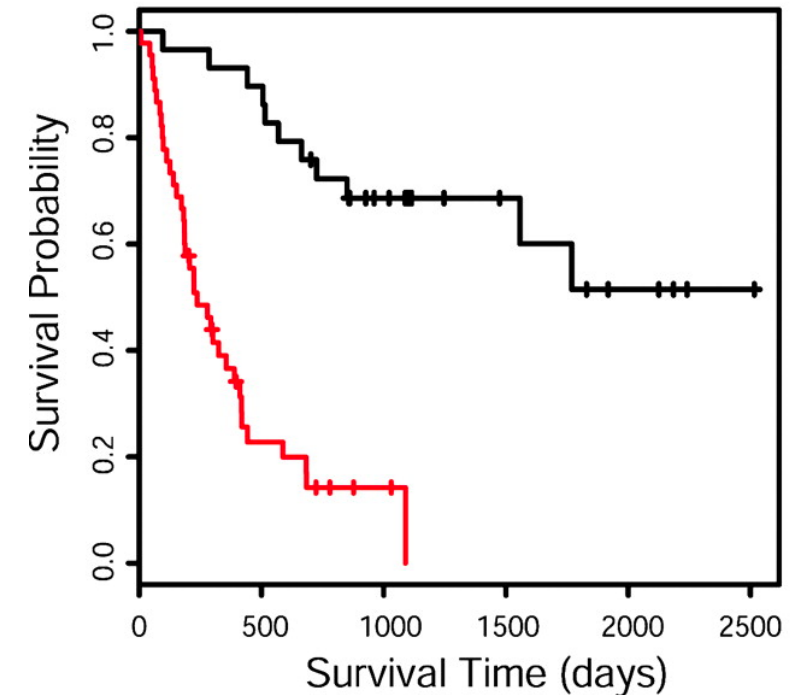
- A pathologist looks at the tissue under a microscope and grade how different the cancer cells look compared to normal, healthy cells.
- Cancer grading is an **image classification problem** where the image should be reasonably large to capture region of interests.



# Application of AI in CP

## Survival Analysis

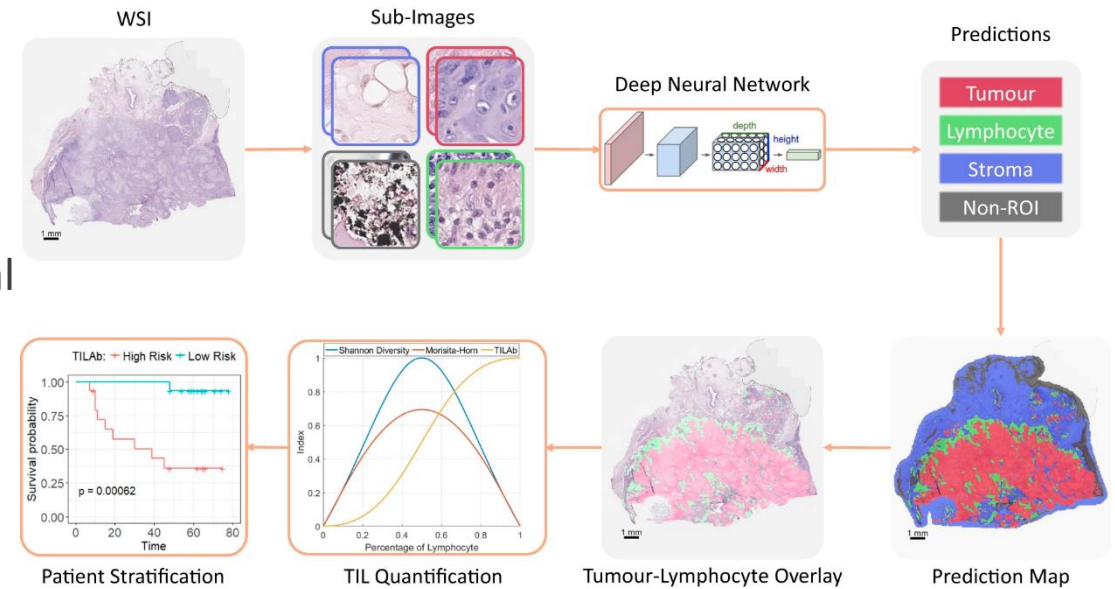
- A statistician analyze the clinical and pathological parameters of a patients and develop a mathematical model to predict the probability of survival for a certain period of time



# Application of AI in CP

## Survival Analysis

- A statistician analyze the clinical and pathological parameters of a patients and develop a mathematical model to predict the probability of survival for a certain period of time
- Instead of relying only on clinical and pathological parameters we can use AI based methods to find novel feature which related to patient survival



# Importance of AI in CP

## Workload

- Cancer detection in a WSI requires significant amount of time (4-5 minutes)
- There could be multiple WSIs for a single case
- Number of cancer cases is increasing globally, and the number pathologist is decreasing in the US
- AI based cancer detection can reduce pathologist workload

## Consistency in Detection

- Two different pathologist may assign different diagnosis label to same case (inter observer variability)
- Same pathologist may assign different diagnosis label to same case at different time (intra observer variability)
- AI based methods will be deterministic and will assign same label to same case every time

# Importance of AI in CP

## Accurate Prediction

- AI based methods are more accurate in some CP tasks e.g., tumor segmentation, cell detection/counting

## Discovering New Clinicopathological Relationships

- Pathologist usually evaluate each case based on predefined set of parameters e.g., tumor stage or grade
- AI has the potential to find novel patterns which may lead to precise treatment plan for each patient

# AI based CP Workflow

## Preprocessing

- Patch extraction from WSIs
- Stain/Color Normalization
- Data Augmentation

## AI Model

- Selection of Suitable Network Architecture

## Post Processing

- Patch prediction integration to generate WSI level prediction



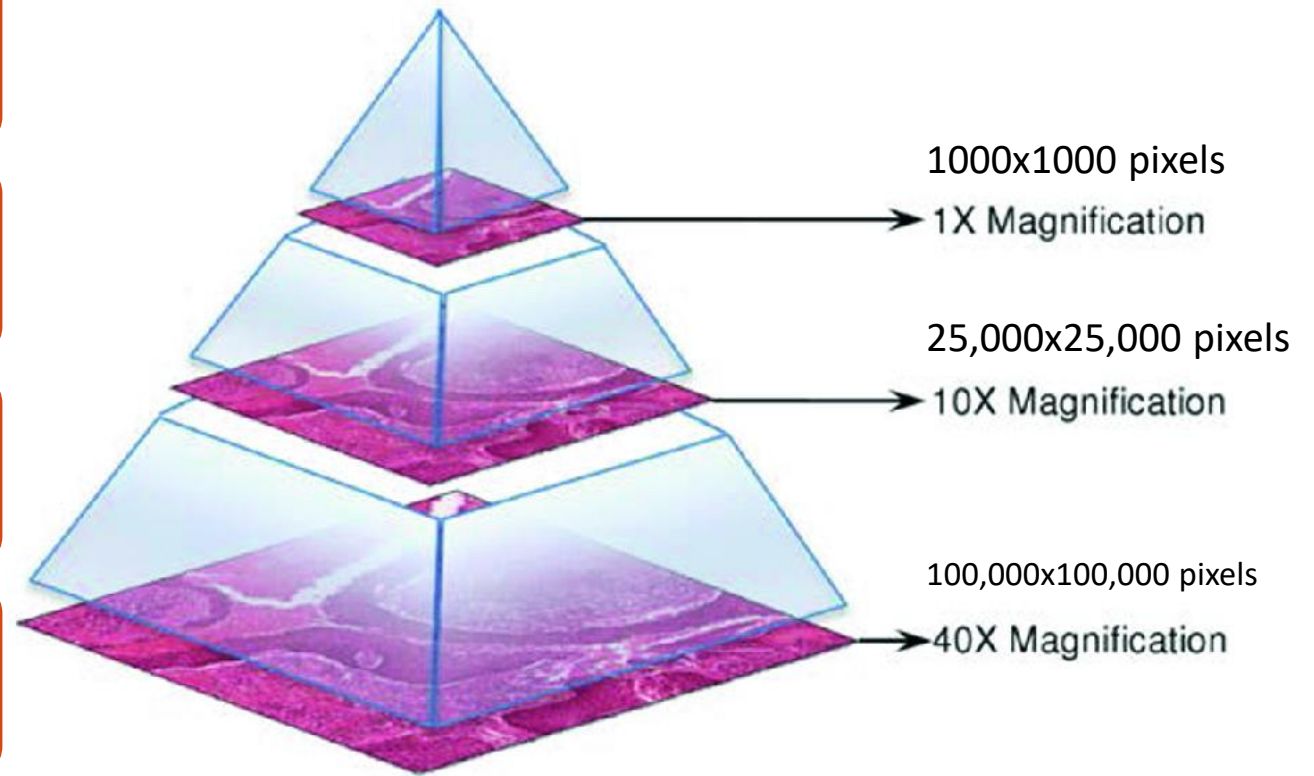
# Preprocessing - Patch extraction from WSIs

WSIs are very large and cannot be directly used for training

Need to select a magnification level to extract patches

Model trained on one magnification and tested on another magnification usually shows inferior performance

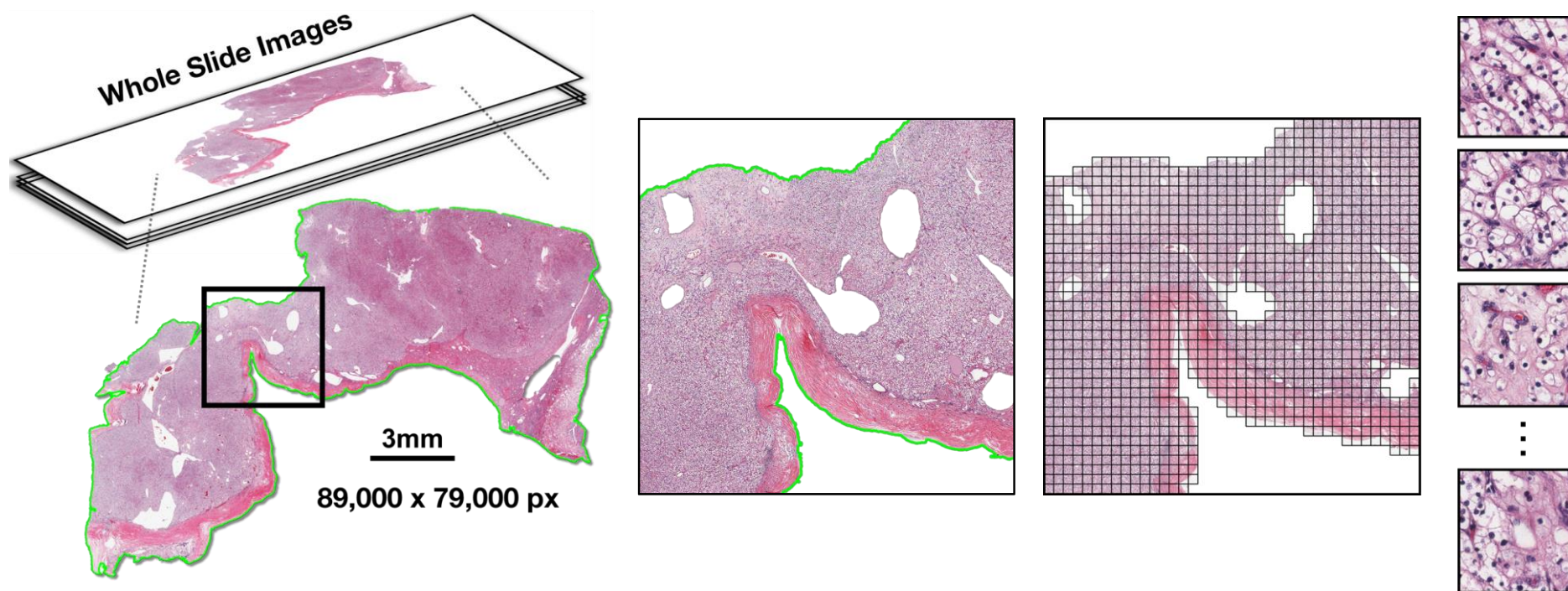
Need to select subset of patches from each WSIs as each WSI may contains tens of thousands of patches





# Preprocessing - Patch extraction from WSIs

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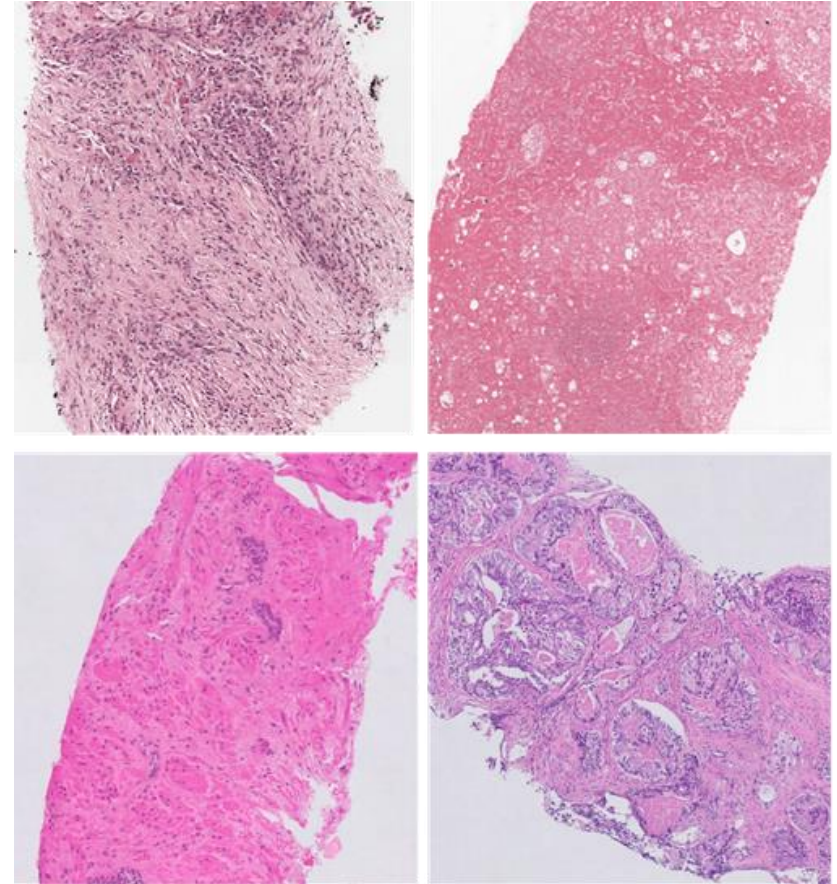
# Preprocessing - Stain/Color Normalization

WSIs from different institutions/hospitals may have significant color variation due to difference in slide preparation or scanning protocols

Color normalization helps in better performance during test time

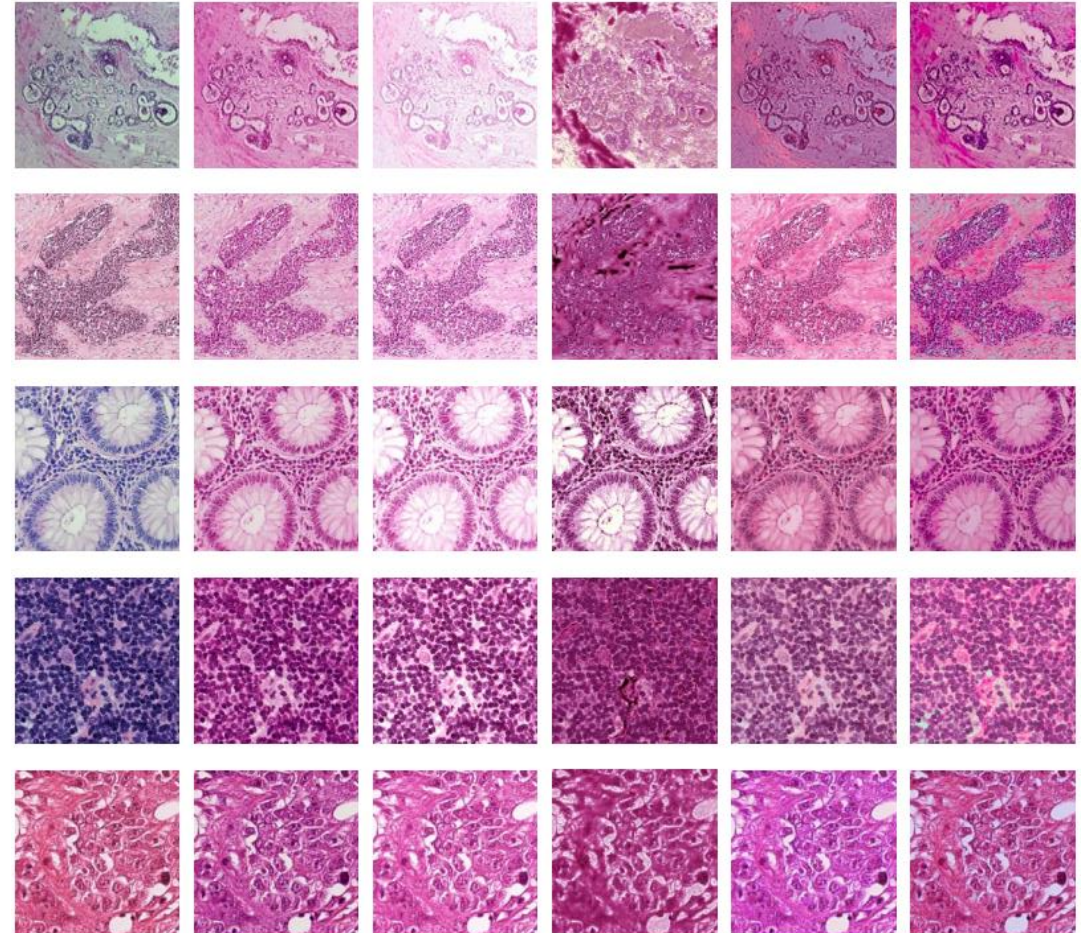
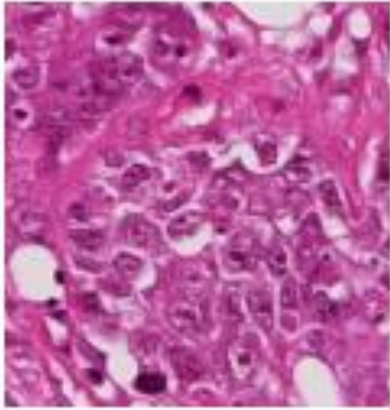
Model trained on color normalized data requires color normalized images at test time

Random color augmentation during training also helps in achieving robust model





# Preprocessing - Stain/Color Normalization

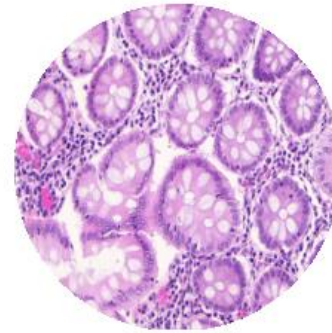


# Preprocessing - Data Augmentation

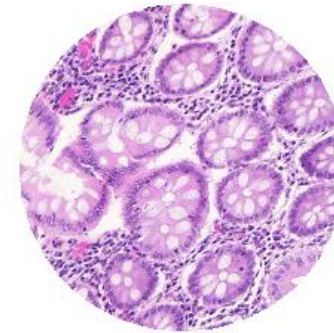
A tissue in a WSI is placed without any consideration of its orientation

CP model should be invariant to rotation and flipping

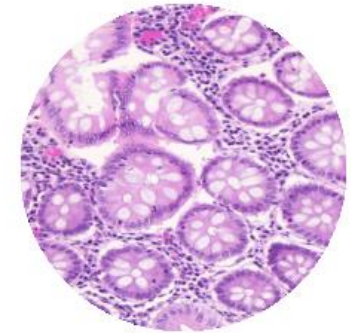
Random rotation and flipping during model training is important to achieve more robust model



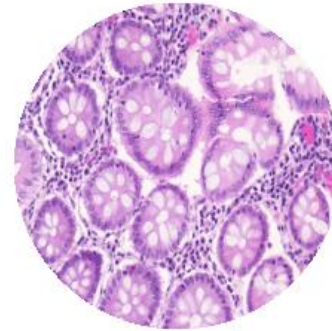
Original



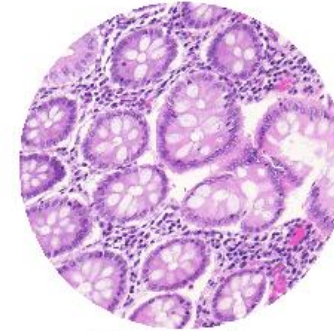
45° rotation



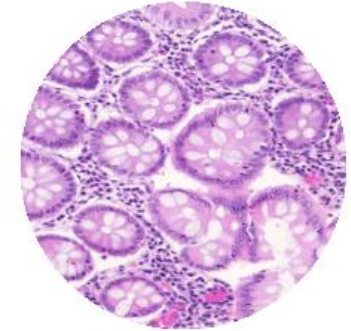
90° rotation



180° rotation



225° rotation



270° rotation

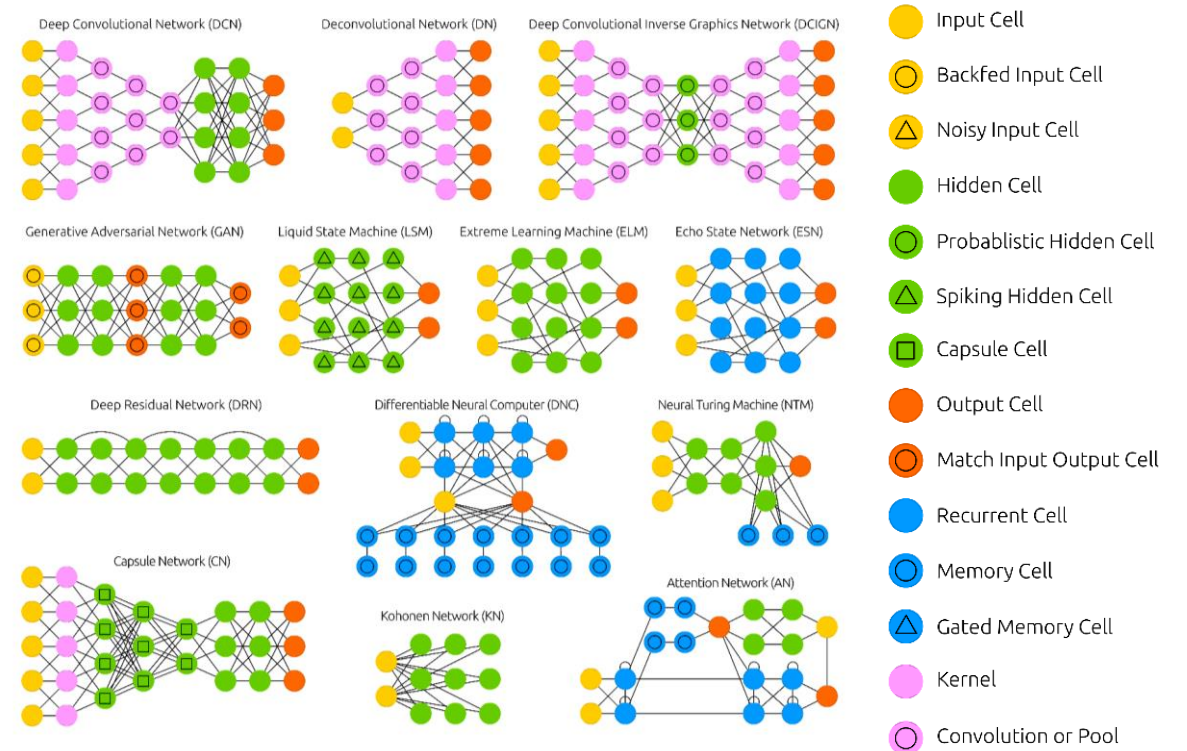


# AI Model

Different CP problems require different types of network architecture

Standard networks proposed for natural images (Resnet50, Inception-v3, Deeplab, etc) work well for common CP problems e.g., cancer classification or segmentation

Some CP problems require technical novelty to incorporate domain knowledge to get better performance



# AI Model



Convolutional Neural  
Network

Classification and  
Segmentation



Auto-Encoder

Representation Learning  
Unsupervised Learning



Generative Adversarial  
Networks (GANs)

Synthetic dataset creation  
Domain adoption



Long Short-Term Memory  
(LSTM) Networks

Survival analysis

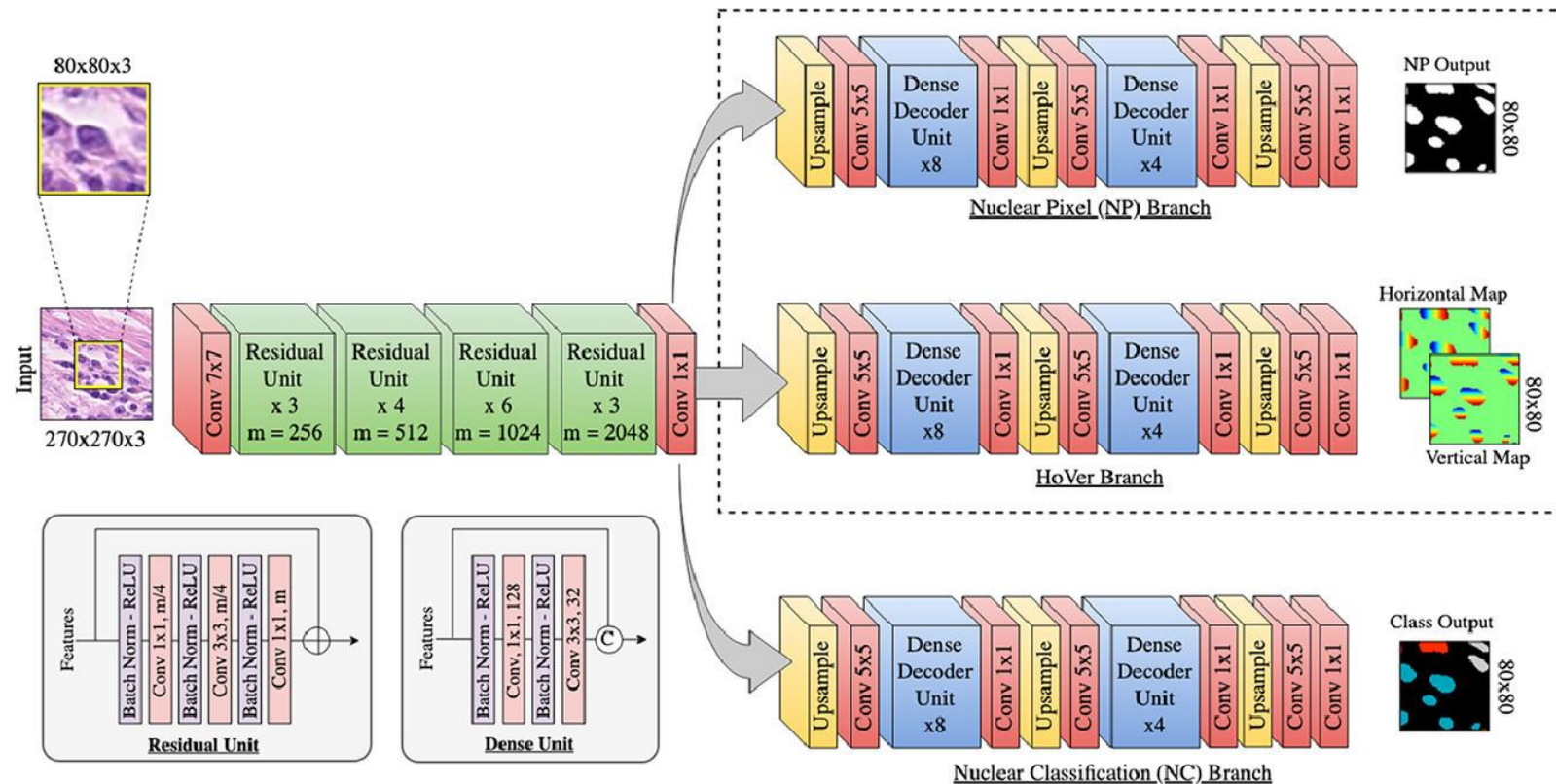


Weekly Supervised Learning

WSI level classification

# AI Model – Cell Segmentation and Classification

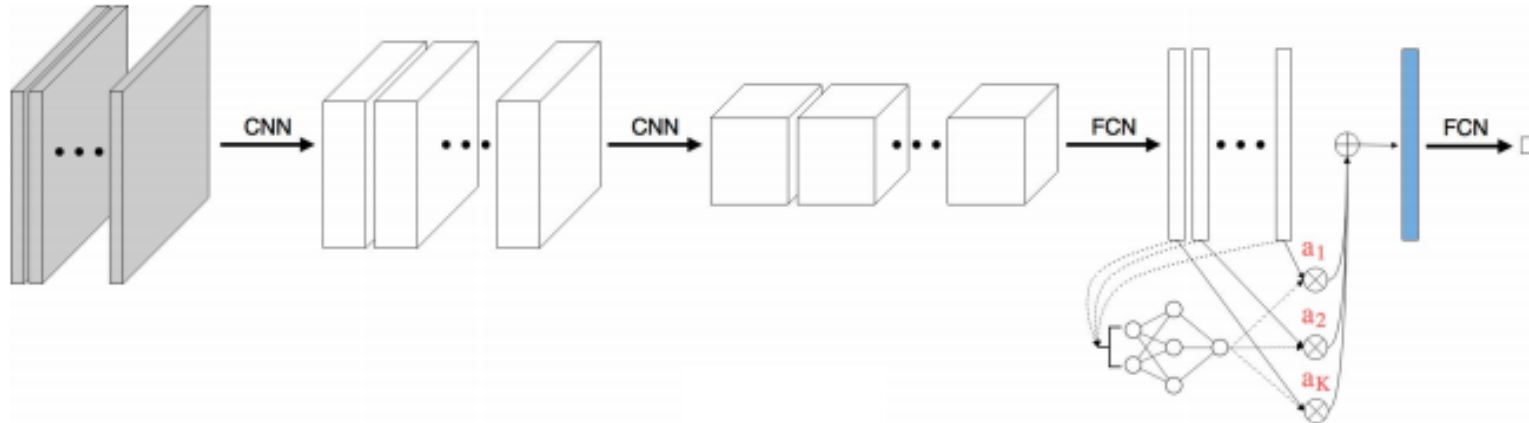
**HoverNet:** Simultaneous segmentation and classification of nuclei in multi-tissue histology images



# AI Model – WSI Level Classification

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## Attention-based Deep Multiple Instance Learning



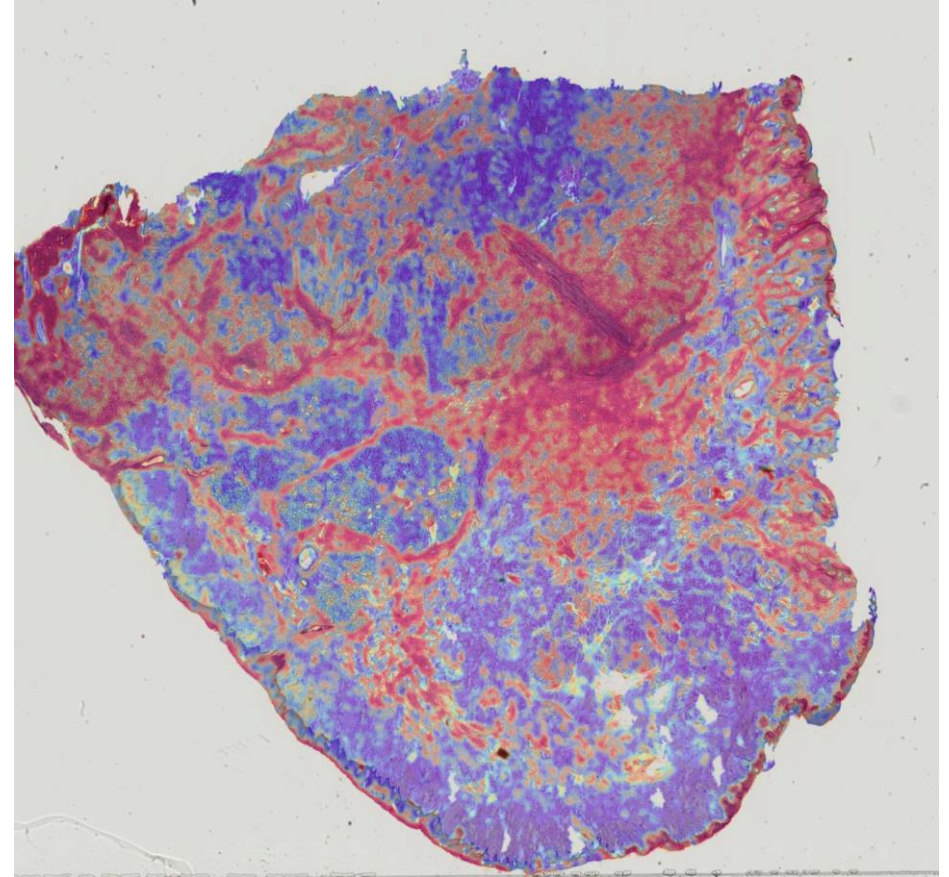


# Post Processing

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Require stitching of patch level prediction into a WSI level prediction map

If CP problem requires a WSI level label then some integration strategy will be required to accumulate patch level prediction



# Top Ranked Publication in CP

Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer

- Journal of the American Medical Association
- Impact Factor: 56.3

AI-based pathology predicts origins for cancers of unknown primary

- Journal: Nature
- Impact Factor: 54.6

Geospatial immune variability illuminates differential evolution of lung adenocarcinoma

- Journal: Nature Medicine
- Impact Factor: 49.2

Data-efficient and weakly supervised computational pathology on whole-slide images

- Journal: Nature Biomedical Engineering
- Impact Factor: 26.355

Top Computer Vision Journal

- IEEE Transactions on Pattern Analysis and Machine Intelligence
- Impact Factor: 16.4

# Challenges



Availability of Imaging Datasets



Ethical Approval



Limited Ground Truth Labels/ Annotations



Disk Storage



Computational Resources

# Challenges – Availability of Imaging Datasets

There are many publically available histology datasets

Dateset of rare type of cancers are quite small

Datasets with balanced number of samples are not readily available

Curation of clean and balanced dataset is challenging and expensive

| Tissue        | <i>n</i> | Tissue        | <i>n</i> |
|---------------|----------|---------------|----------|
| Breast        | 1092     | Ovary         | 376      |
| Lung          | 1016     | Liver         | 371      |
| Kidney        | 885      | Cervix        | 304      |
| Brain         | 677      | Soft tissue   | 259      |
| Colorectal    | 623      | Adrenal gland | 258      |
| Uterus        | 611      | Pancreas      | 177      |
| Thyroid       | 502      | Esophagus     | 164      |
| Head and Neck | 501      | Bone marrow   | 151      |
| Prostate      | 495      | Eye           | 80       |
| Skin          | 468      | Lymph nodes   | 48       |
| Bladder       | 408      | Bile duct     | 36       |
| Stomach       | 380      |               |          |

# Challenges – Ethical Approval

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Histology datasets consist of human tissues

One can only use these datasets after taking the **informed consent** of patients

Datasets should not contain any information which can be used to disclose the patient's identity



# Challenges – Limited Ground Truth

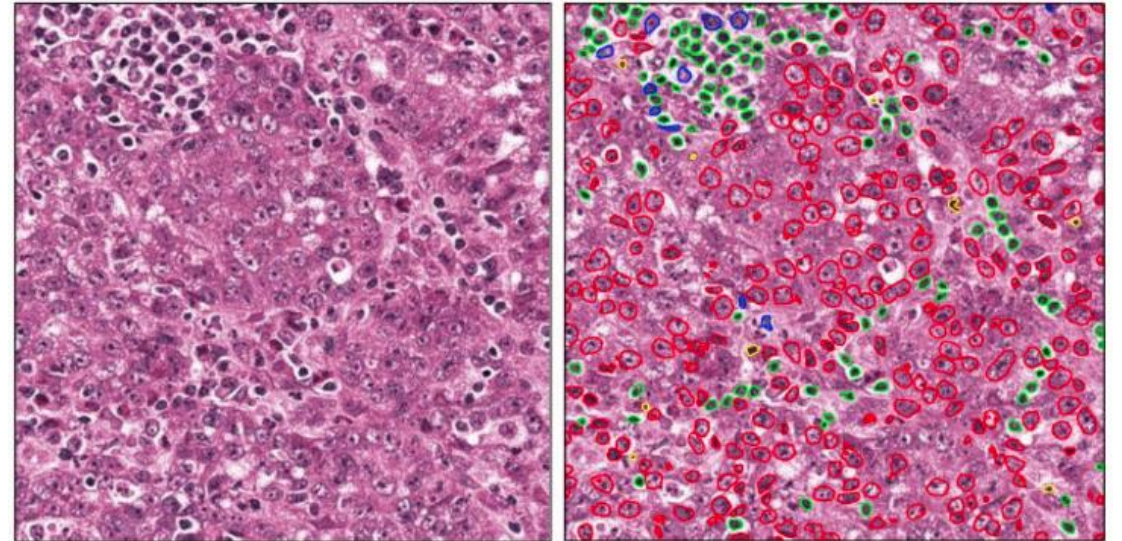
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Unlike natural images, only trained pathologist can mark ground truth (cancer) in histology images

Pixel/Cell level ground truth marking is the most labourious task as there are hundreds of thousands of pixels/cells in each WSI

There is known inter-observer variability issue in ground truth marking

WSI level ground truth is the most readily available form of ground truth



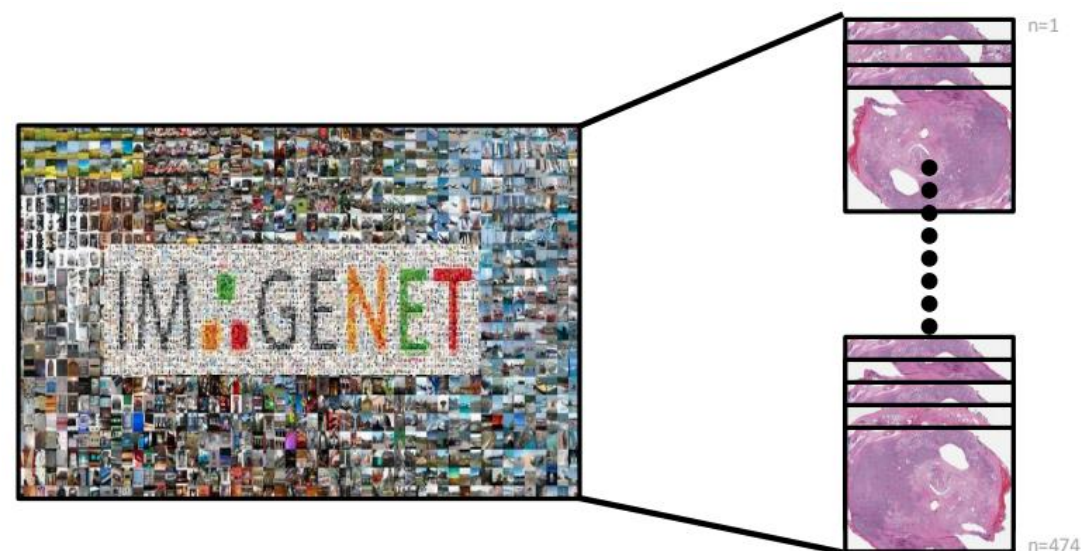


# Challenges – Disk Storage

Storing a WSIs based dataset on a local machines required huge amount of disk storage

The disk storage required for ImageNet dataset is less the storage required for 500 WSIs

One of the largest WSIs public dataset (TCGA) required **1.2 Petabyte** disk storage



**All of ImageNet**  
 $482 \times 415 \times 14,197,122$   
 $= 2.8 \text{ trillion pixels}$

**474 Whole Slides**  
 $100,000 \times 60,000 \times 474$   
 $= 2.8 \text{ trillion pixels}$

# Challenges – Computational Resources

AI based CP model also require huge computational resources both for model training and inference

Big AI based pathology labs and companys use super comptuers (Nvidia DGX2 or A100) for CP model training and inference

Small CP usually used pretrained features for model training of very large datasets

## SYSTEM SPECIFICATIONS

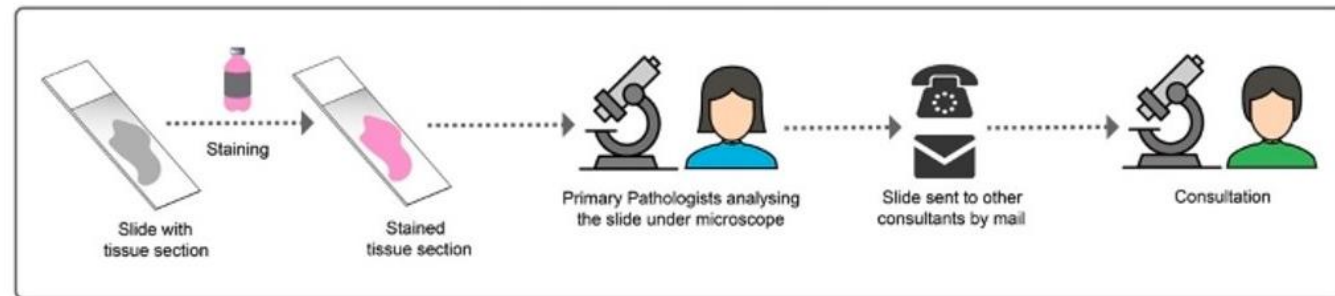
|                     |   |
|---------------------|---|
| GPUs                | 16X NVIDIA® Tesla® V100   |
| GPU Memory          | 512GB total   |
| Performance         | 2 petaFLOPS   |
| NVIDIA CUDA® Cores  | 81920   |
| NVIDIA Tensor Cores | 10240   |
| NVSwitches          | 12  |
| Maximum Power Usage | 10kW  |
| CPU                 | Dual Intel Xeon Platinum<br>8168, 2.7 GHz, 24-cores                       |
| System Memory       | 1.5TB   |
| Network             | 8X 100Gb/sec<br>Infiniband/100GigE<br>Dual 10/25/40/50/100GbE             |
| Storage             | OS: 2X 960GB NVME SSDs<br>Internal Storage: 30TB<br>(8X 3.84TB) NVME SSDs |



# State of CP in Pakistan

Almost all cancer hospital in Pakistan still follow the traditional pathway for cancer diagnosis

There is only whole slide image scanner somewhere in Sindh



# State of CP in Pakistan

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Computer vision labs (in NUST, LUMS, ITU) are working on CP problems using publicly available datasets

Some pathologists are also quite enthusiastic about CP and willing to mark ground truth on publicly available datasets

# State of CP in Pakistan

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Computational resources in CV labs required for large scale CP studies are also not enough

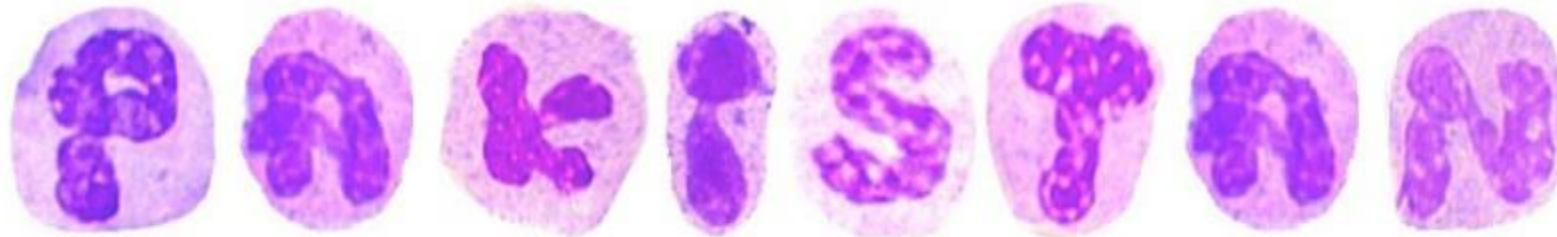
This limitation can be considered as an opportunity to develop light-weight models for CP problems

International CP community has enough computational resources therefore they don't pay much attention to the development of light-weight methods for CP problems

# State of CP in Pakistan

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I have created a group (Digital Pathology - Pakistan) on LinkedIn to link pathologists and computer vision community to build a CP community in Pakistan



# Histopathology Datasets

| Dataset or paper                  | Image size (px)      | # images | Stain   | Disease           | Additional data   | Potential usage                                  |
|-----------------------------------|----------------------|----------|---------|-------------------|---|--|
| KIMIA960 [87,88]                  | 308×168              | 960      | H&E/IHC | various tissue    |   | Disease classification                           |
| Bio-segmentation [89,90]          | 896×768, 768×512     | 58       | H&E     | Breast cancer     |   | Disease classification                           |
| Bioimaging challenge 2015 [91,92] | 2040×1536            | 269      | H&E     | Breast cancer     |   | Disease classification                           |
| GlaS [23,93]                      | 574–775×430–522      | 165      | H&E     | Colorectal cancer | Mask for gland area   | Gland segmentation                               |
| BreakHis [15,94]                  | 700×460              | 7909     | H&E     | Breast cancer     |   | Disease classification                           |
| Jakob Nikolas et al. [88,95]      | 1000×1000            | 100      | IHC     | Colorectal cancer | Blood vessel count  | Blood vessel detection                           |
| MITOS-ATYPIA-14 [96]              | 1539×1376, 1663×1485 | 4240     | H&E     | Breast cancer     | Coordinates of mitosis with a confidence degree/six criteria to evaluate nuclear atypia | Mitosis detection, nuclear atypia classification |

# Histopathology Datasets

|  |                         |         |     |                   |   |                         |
|--|-------------------------|---------|-----|-------------------|---|-------------------------|
| <b>Kumar et al.</b><br><a href="#">[97,98]</a>       | 1000×1000               | 30      | H&E | Various cancer    | Coordinates of annotated nuclear boundaries | Nuclear segmentation    |
| <b>MITOS 2012</b><br><a href="#">[20,99]</a>         | 2084×2084,<br>2252×2250 | 100     | H&E | Breast cancer     | Coordinates of mitosis                      | Mitosis detection       |
| <b>Janowczyk et al.</b><br><a href="#">[100,101]</a> | 1388×1040               | 374     | H&E | Lymphoma          | None  | Disease classification  |
| <b>Janowczyk et al.</b><br><a href="#">[100,101]</a> | 2000×2000               | 311     | H&E | Breast cancer     | Coordinates of mitosis                      | Mitosis detection       |
| <b>Janowczyk et al.</b><br><a href="#">[100,101]</a> | 100×100                 | 100     | H&E | Breast cancer     | Coordinates of lymphocyte                   | Lymphocyte detection    |
| <b>Janowczyk et al.</b><br><a href="#">[100,101]</a> | 1000×1000               | 42      | H&E | Breast cancer     | Mask for epithelium                         | Epithelium segmentation |
| <b>Janowczyk et al.</b><br><a href="#">[100,101]</a> | 2000×2000               | 143     | H&E | Breast cancer     | Mask for nuclei                             | Nuclear segmentation    |
| <b>Janowczyk et al.</b><br><a href="#">[100,101]</a> | 775×522                 | 85      | H&E | Colorectal cancer | Mask for gland area                         | Gland segmentation      |
| <b>Janowczyk et al.</b><br><a href="#">[100,101]</a> | 50×50                   | 277,524 | H&E | Breast cancer     | None  | Tumor detection         |



# Conclusion

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CP is an emerging field in medical image analysis domain

Working in CP does require development of technically novel methods

Knowledge of state-of-the-art AI methods is required to solve clinically important CP problems

# Conclusion

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AI based CP methods have potential to be published in journals with very high impact factor

High impact CP studies require huge computational, storage and human resources

Experience in AI based CP can help in getting a good PhD position/job

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Thank You!

