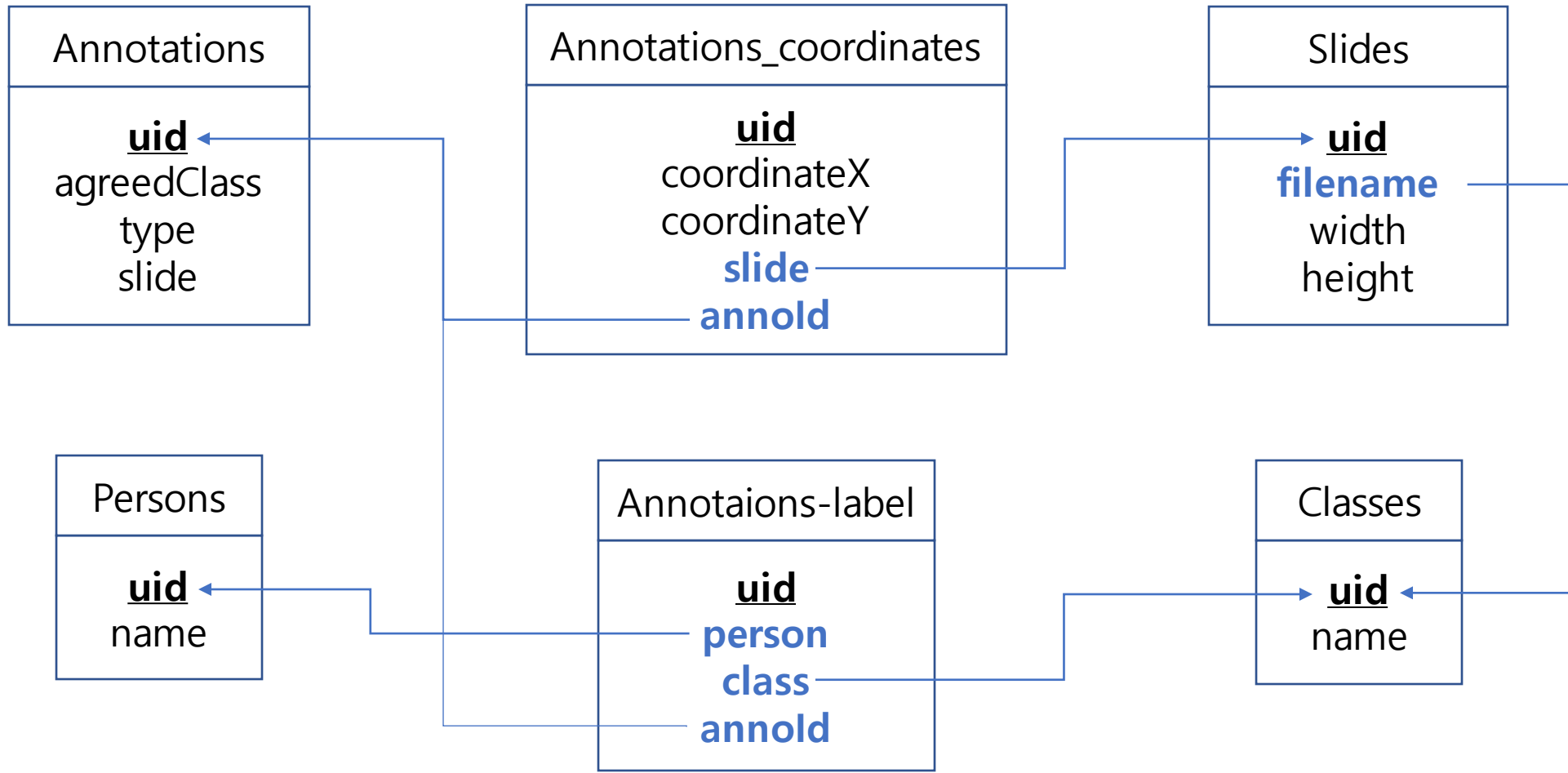


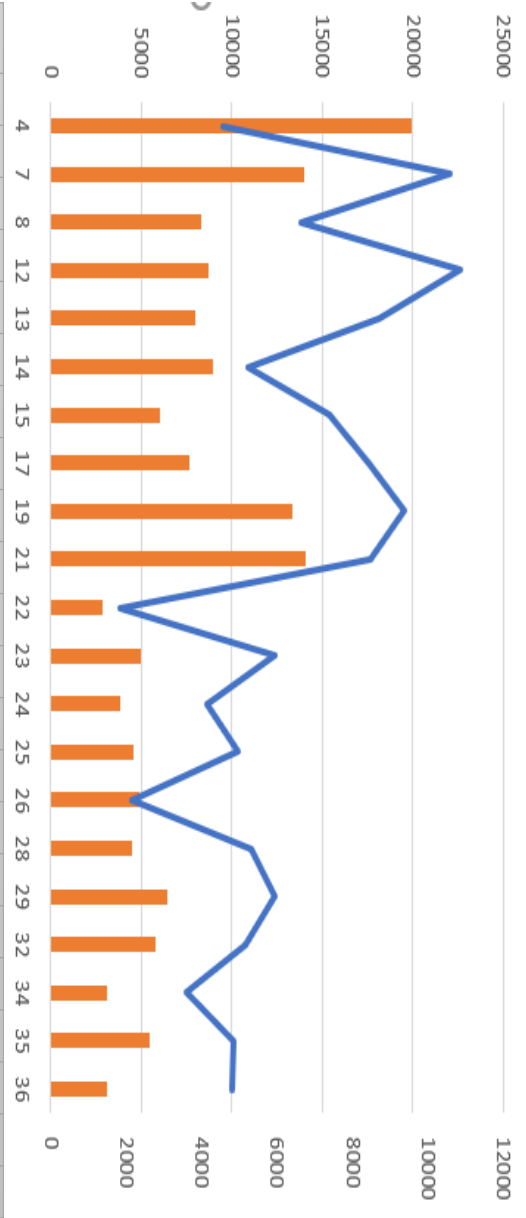
Unique key  
Foreign Key

# Database Schema



# EDA

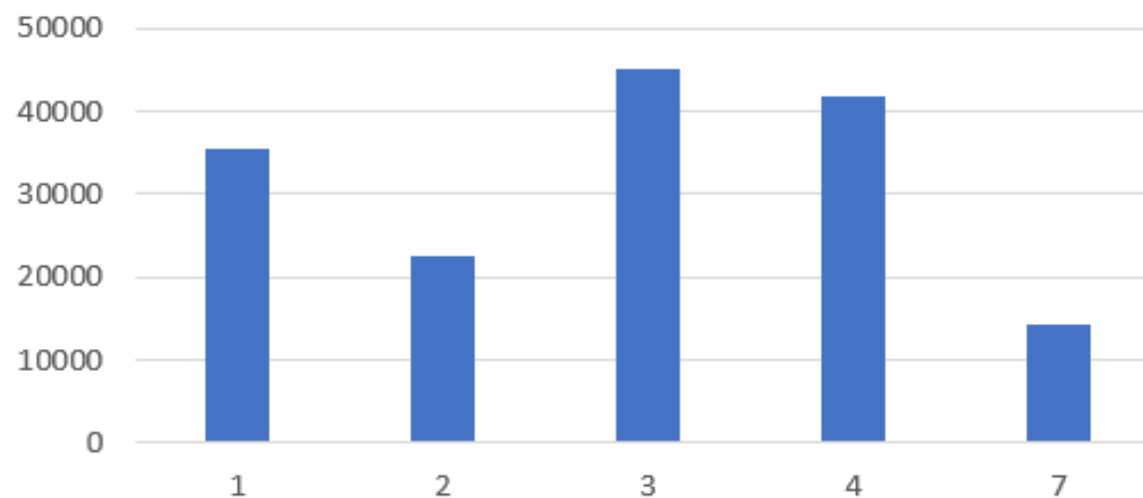
Slide 번호	width	height	Tiles(1000 x 1000)	Abnormal cells
4	82799	54996	4565	19936
7	113399	92597	10602	14040
8	80999	81620	6642	8314
12	127799	84057	10880	8717
13	104399	82678	8715	7991
14	77399	66558	5226	8986
15	88199	82404	7387	6017
17	113399	73675	8436	7656
19	100799	92632	9393	13390
21	109799	76571	8470	14057
22	23399	76964	1848	2901
23	89999	65400	5940	4997
24	82799	49066	4150	3864
25	55799	88262	4984	4622
26	52199	40646	2173	4889
28	88199	59153	5340	4541
29	77399	75215	5928	6457
32	68400	74760	5175	5776
34	70199	50863	3621	3153
35	62999	76054	4851	5454
36	71999	66251	4824	3154
			총	158912



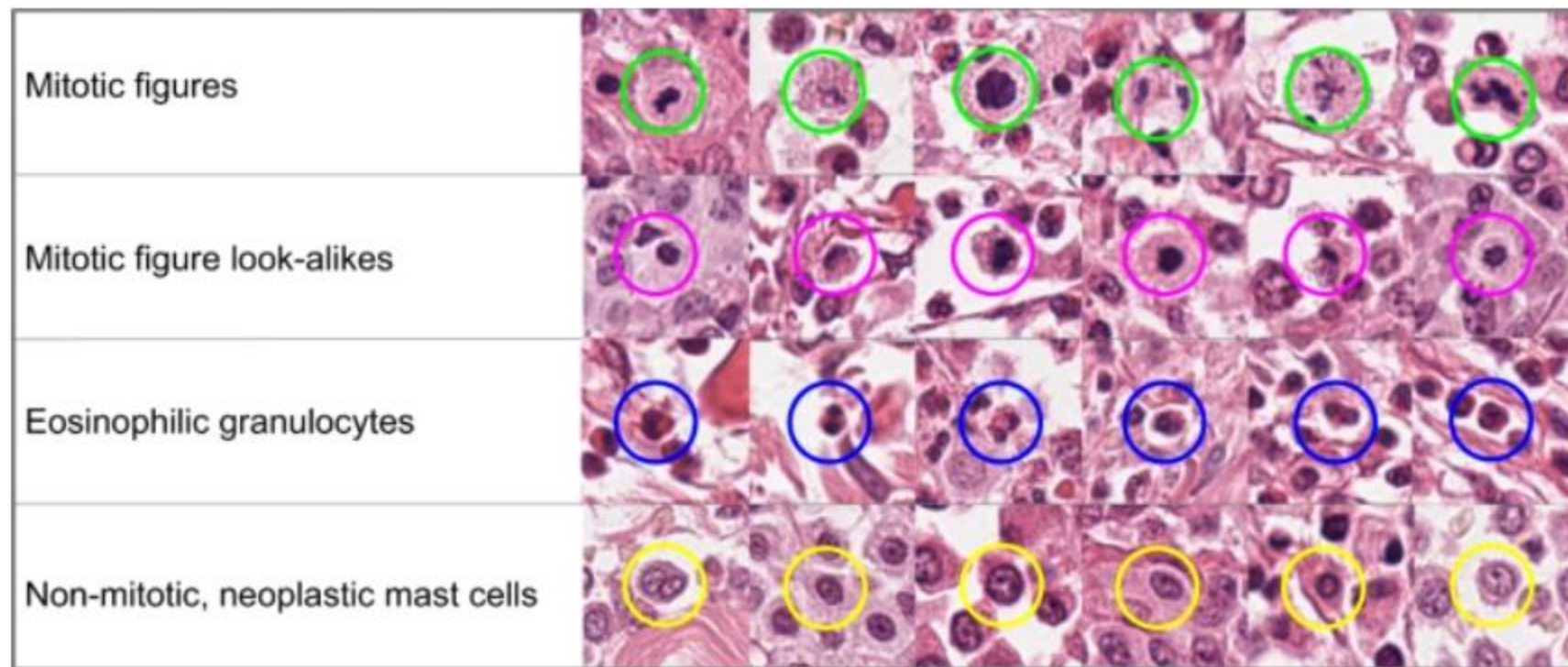
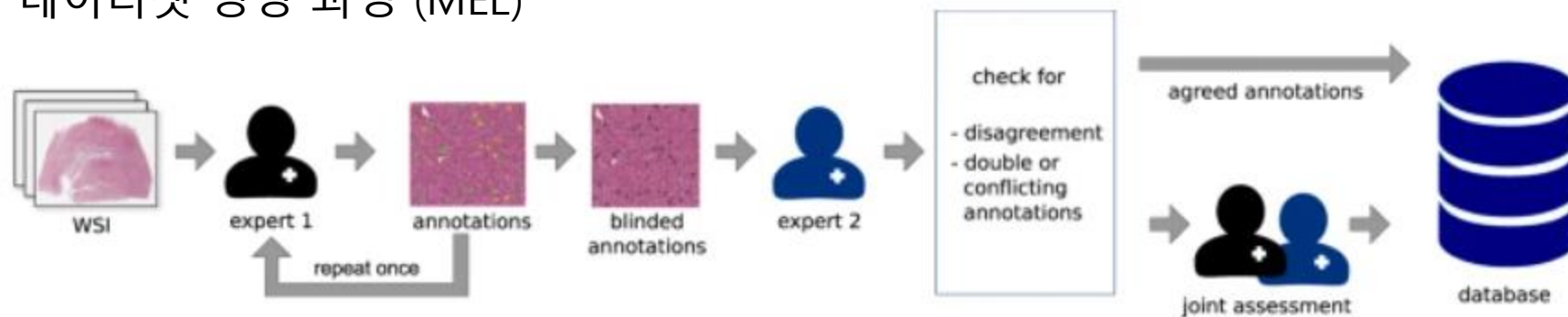
# EDA

Classes	Cells
1	35331
2	22404
3	45179
4	41658
5	0
6	0
7	14340
합계	158912

1	granulocyte
2	mitotic figure
3	tumor cell
4	other/ambiguous cells
5	binucleated cell
6	multinukleated cell
7	Mitotic figure lookalike



## 데이터셋 생성 과정 (MEL)



MEL - manually, expert-labelled dataset - 기존 전문가 데이터셋

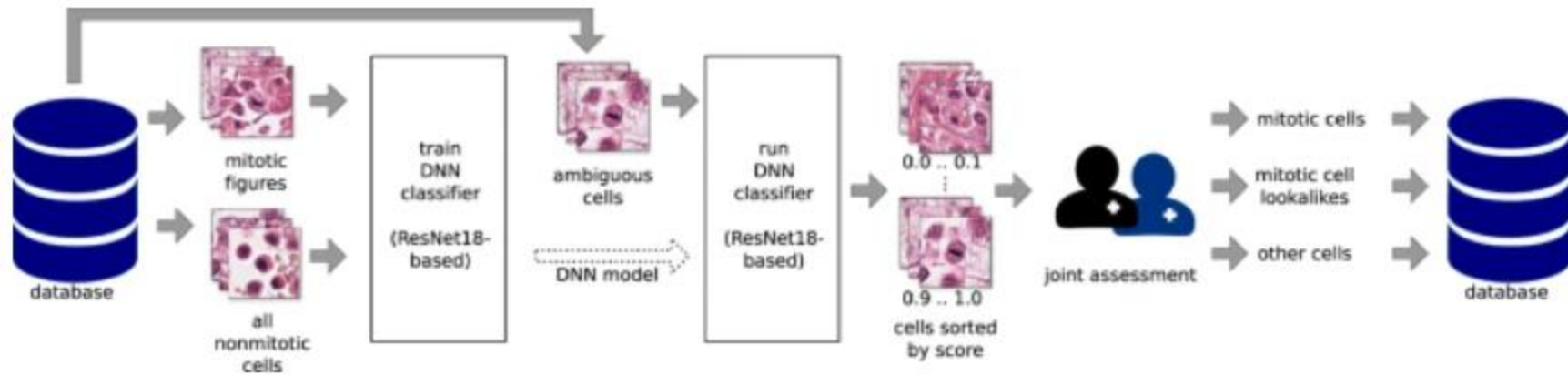
이걸 변형시켜서

HEAL - Hard-example augmented expert labelled dataset variant  
증강 전문가 데이터셋 1

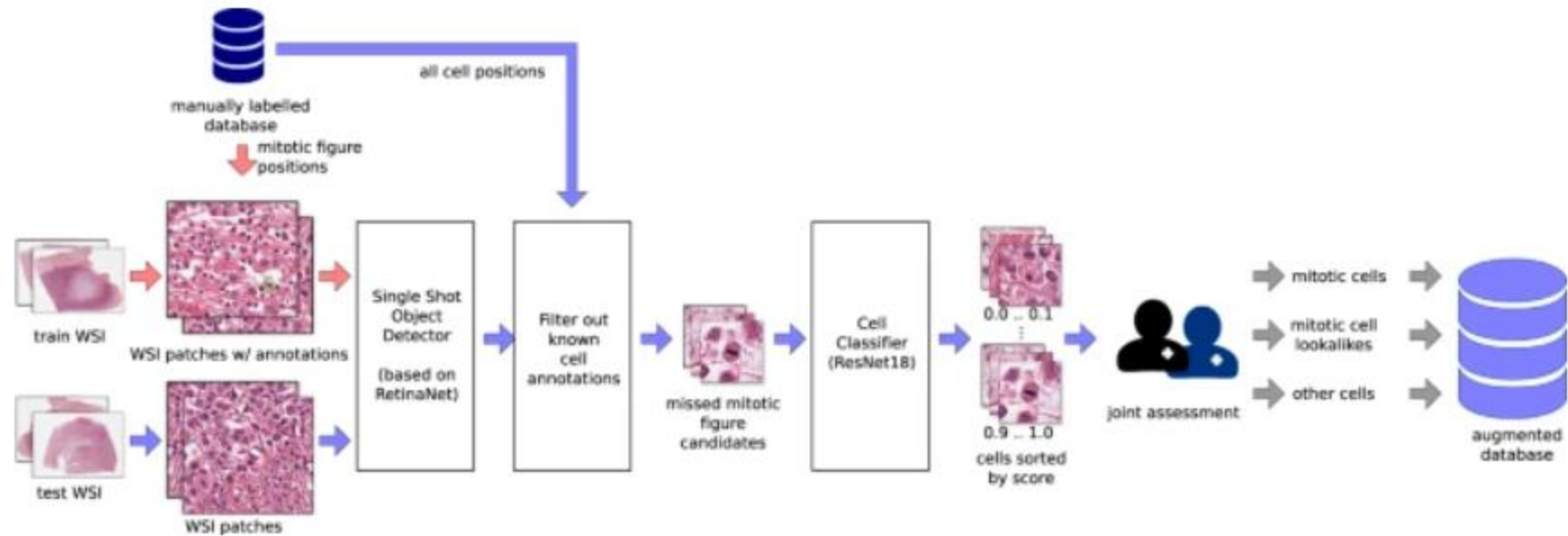
ODAEL - Object-detection augmented expert labelled dataset variant  
잠재적 유사 분열 figure을 DeepLearning을 이용해 추가로 제안, 전문가가 데이터 세트의 다른 그룹으로 등급을 지정하고 할당.

granulocyte - 과립구 - 세포질에 과립이 있는 백혈구

## 모호 클래스 데이터셋 결정 과정(HEAL)

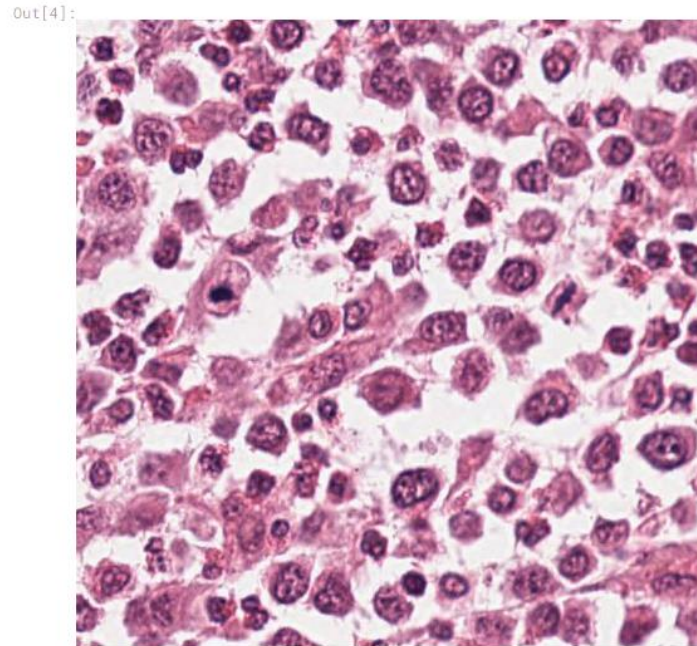


## 잠재적 유사분열 클래스 데이터셋 결정 과정(ODEAL)



# Tiling, Labeling

```
In [4]: ds = ReadableDicomDataset('/kaggle/input/mitosis-wsi-ccmct-training-set/fff27b79894fe0157b08.dcm')
location=(69700,17100)
size=(500,500)
img = Image.fromarray(ds.read_region(location=location, size=size))
img
```



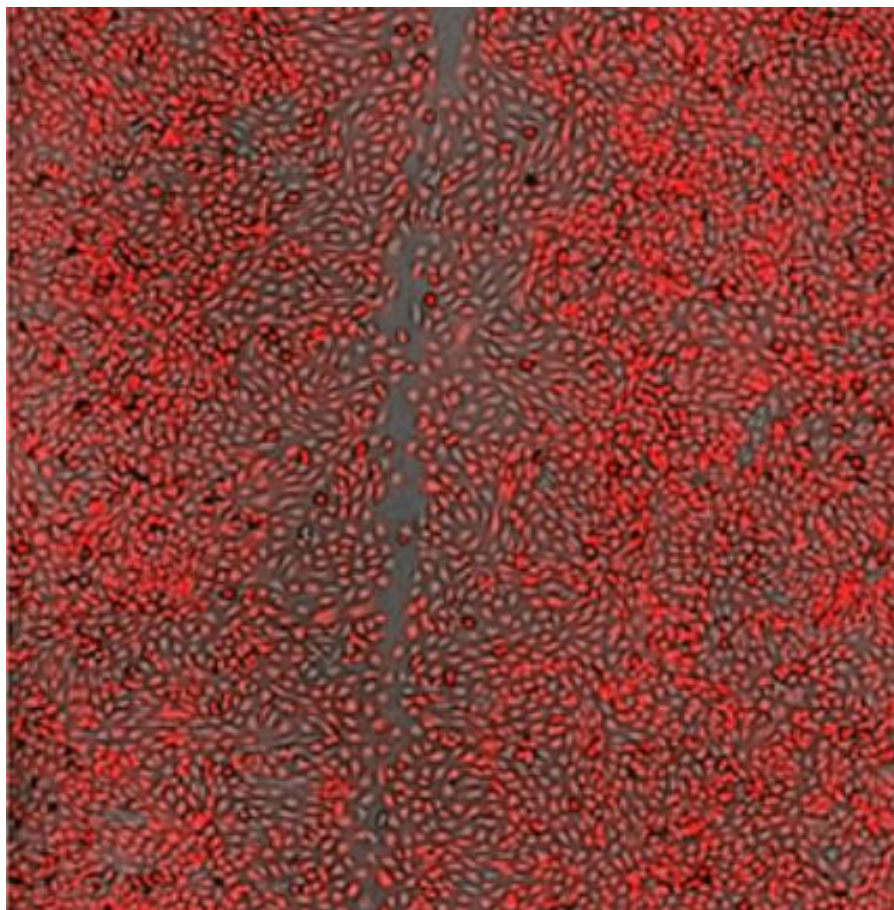
```
In [2]: import sqlite3
DB = sqlite3.connect('/kaggle/input/mitosis-wsi-ccmct-training-set/MITOS_WSI_CCMCT_ODAEL_train_
dcm.sqlite')
cur = DB.cursor()

cells = cur.execute(f"""SELECT coordinateX-{location[0]}, coordinateY-{location[1]}, annoId
                        from Annotations_coordinates where slide=={slide[0]} and
                        coordinateX>{location[0]} and coordinateX<{location[0]+size[0]} and
                        coordinateY>{location[1]} and coordinateY<{location[1]+size[1]}""").fetchall()
```



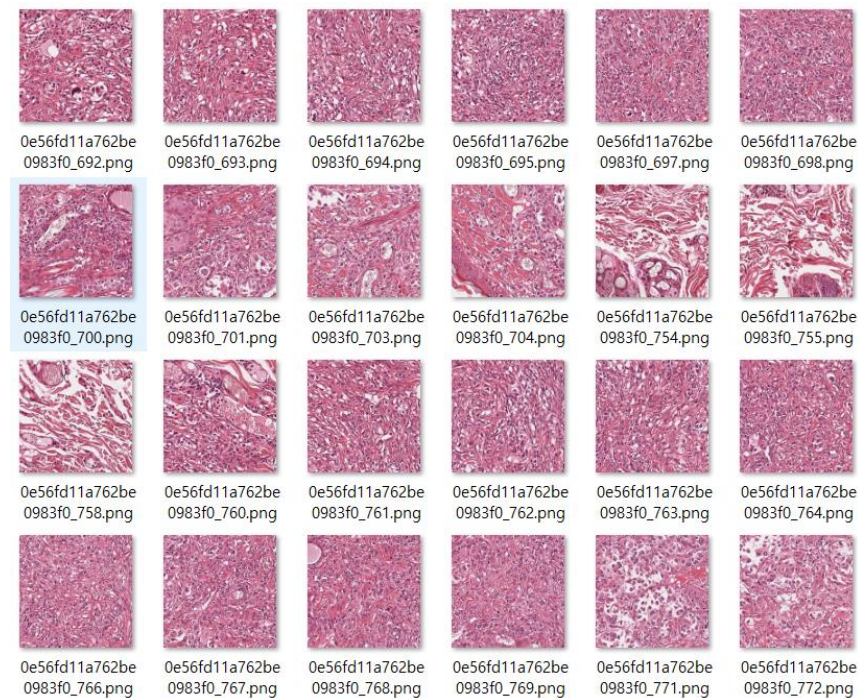
# Large Scale Images

.DCM

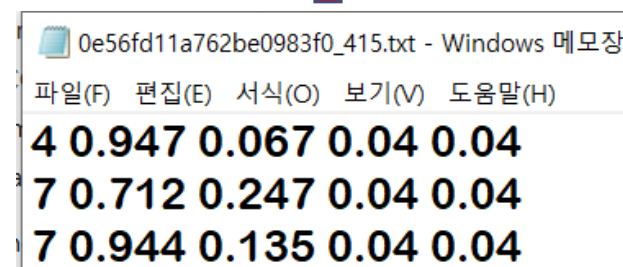


# Tiled Images

.png (640 x 640)



labels  
.txt

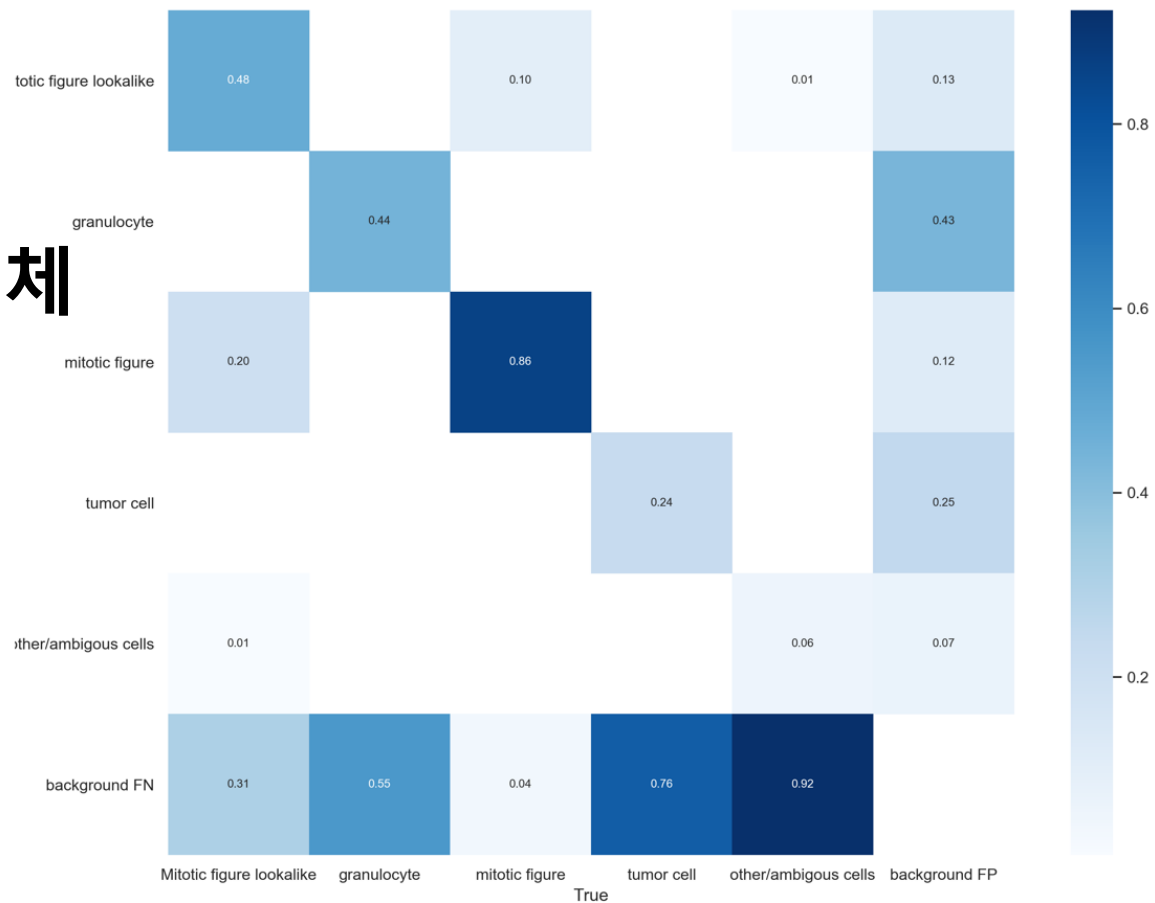




# Yolo\_v5

## Imgsz-640 / epochs-100

## Imgsz-320 / epochs-250 교체



연구기관 결과 : Accuracy 0.91

Actual	pred. mitotic fig.	pred. mitotic fig. look-alike	pred. granulocyte	pred. tumor cell
Mitotic figure	19478	2985	10	3
Mitotic figure look-alike	2942	10582	57	44
Granulocyte	1	66	16011	30
Tumor cell	3	92	53	20651

# 개 비만 세포 종양 (CMCT)

예후, 기수 판별에 MC(Mitotic count)가 주요 요소로 작용

MC - 현미경 10배율 당 유사분열체 수

AgNOR - 세포주기 진행속도

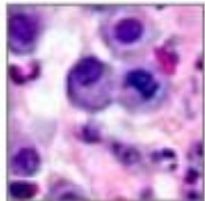
Ni67 - 성장을 식별하는 면역조직화학(IHC)방법 분수

AG67 - AgNor, Ni67 측정에서 얻을수 있는 인자

...

## Mitotic count

(previously referred to as  
"mitotic index")



Actively dividing  
neoplastic mast  
cell

- MC < 7: indicates a low-grade CMCT (Kiupel system):
  - MST: > 2 years
  - 5% of dogs died due to MCT-associated disease
  - 20% developed additional MCTs
- MC ≥ 7: indicates a high-grade CMCT (Kiupel system):
  - MST: < 4 months
  - 90% of dogs died due to MCT-associated disease
  - 70% developed metastasis

- MC > 5:
  - MST of approximately 2 months (compared to 70 months in case of CMCTs with MC lower than 5)
- 91% specificity of identifying aggressive CMCTs (with 79% diagnostic accuracy)

## 현재 데이터에서 MC(Mitotic count) 측정

was performed by a linear scanner (ScanScope CS2, Leica, Germany) in one focal plane by default settings at a magnification of 400x (image resolution:  $0.25 \mu\text{m}/\text{pixel}$ ), using an Olympus UPlanSAPO 20x lens (field number = 26.5, numerical aperture = 0.75).

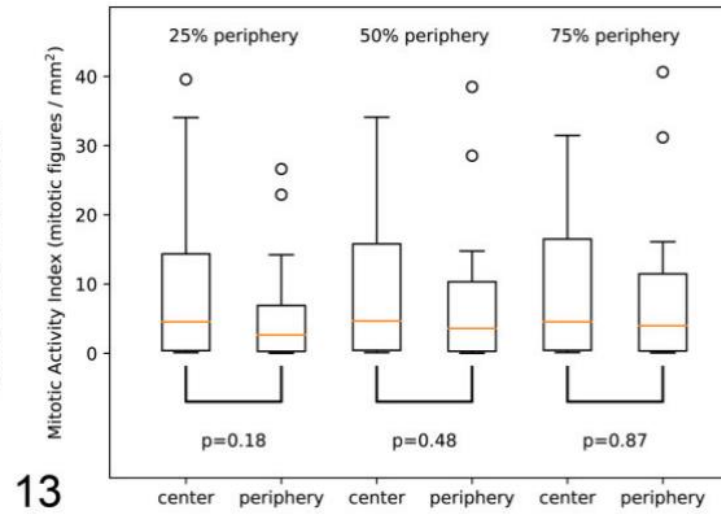
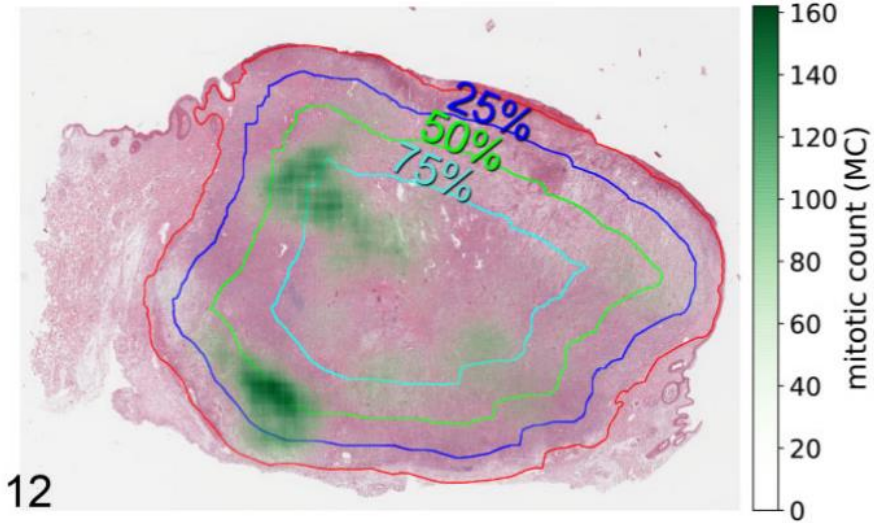
Manually expert labelled (MFL) dataset

Area per high-power field for some microscope types:

- **Olympus** BX50, BX40 or BH2 or AO:  $0.096 \text{ mm}^2$ <sup>[1]</sup>
- **AO** with 10x eyepiece:  $0.12 \text{ mm}^2$ <sup>[1]</sup>
- **Olympus** with 10x eyepiece:  $0.16 \text{ mm}^2$ <sup>[1]</sup>
- **Nikon Eclipse E400** with 10x eyepiece and 40x objective:  $0.25 \text{ mm}^2$ <sup>[2]</sup>
- **Leitz Ortholux**:  $0.27 \text{ mm}^2$ <sup>[1]</sup>
- **Leitz Diaplan**:  $0.31 \text{ mm}^2$ <sup>[1]</sup>

640 x 640당 평균 몇 개의  
Mitotic cell 이 있는가

## 특정 범위에 Mitotic Cell이 얼마나 분포되어 있는지도 기수 판별의 주 요소 -> MC 분포 시각화





# 출처

<https://www.nature.com/articles/s41597-019-0290-4>

<https://www.kaggle.com/marcaubreville/first-steps-with-the-mitos-wsi-ccmct-data-set>

# 논문

Histopathology and prognostic panels to aid in the diagnosis and management



canine-mct.pdf

Computerized Calculation of Mitotic Count Distribution in Canine Cutaneous Mast Cell Tumor Sections: Mitotic Count Is Area Dependent

## 과정

전처리 – dcm to png (640, 320, 256)

1. yolov5s – img640 epochs 100
2. yolov5s – img320 epochs 230
3. yolov5l – img320 epochs 300

## To do

1. ~~yolov5 + Efficient Net < -보류~~
2. ~~Faster R-CNN < M2det로 전환, 진행중~~
3. ~~None 라벨 추가 < M2det 테스트 예정, 이후 yolo~~
4. 상업화 – mitotic cell visualization, mitotic count > 이후 과제, 현재는 성능에 집중
5. 모델링 데이터 전부 끌어와서 비교