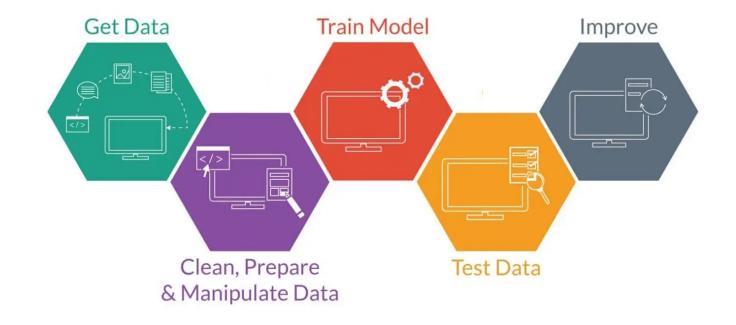
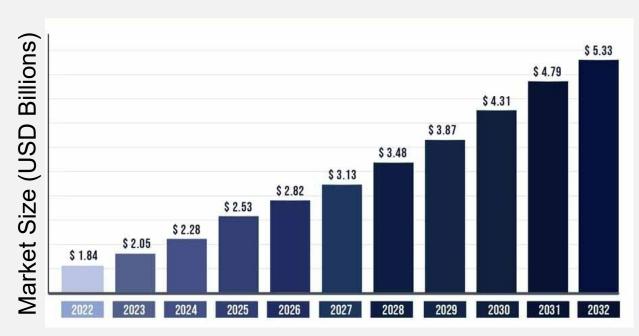
ML IN DIGITAL PATHOLOGY

Yuan Nghiem Leo Grant Berman Albert Bulik



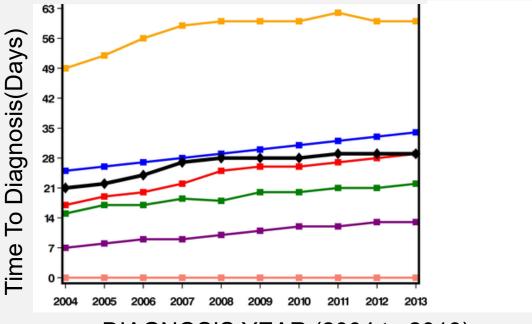
PROBLEM STATEMENT

The demand for cancer diagnosis is increasing.



YEAR (2022 to 2032)

As a result, time to treatment is increasing.



DIAGNOSIS YEAR (2004 to 2013)

SOURCE

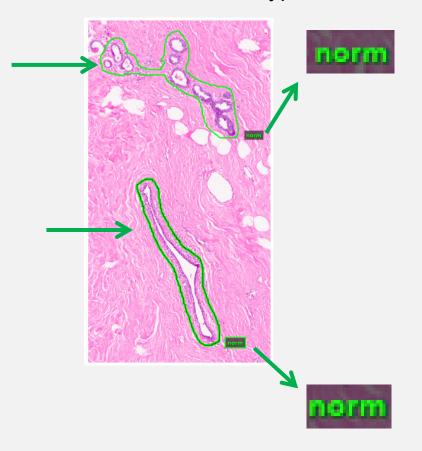
SOURCE

TEMPLE UNIVERSITY HEALTH DIGITAL PATHOLOGY (TUHDP) CORPUS

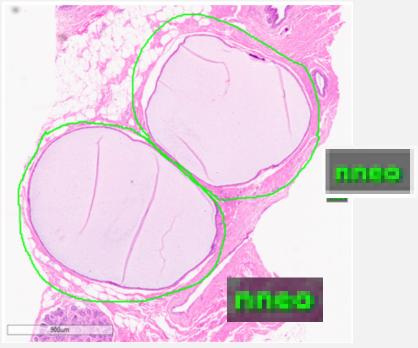


LABELED DATA TYPES

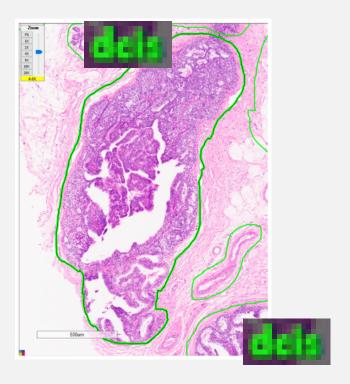
Non-Cancerous Types



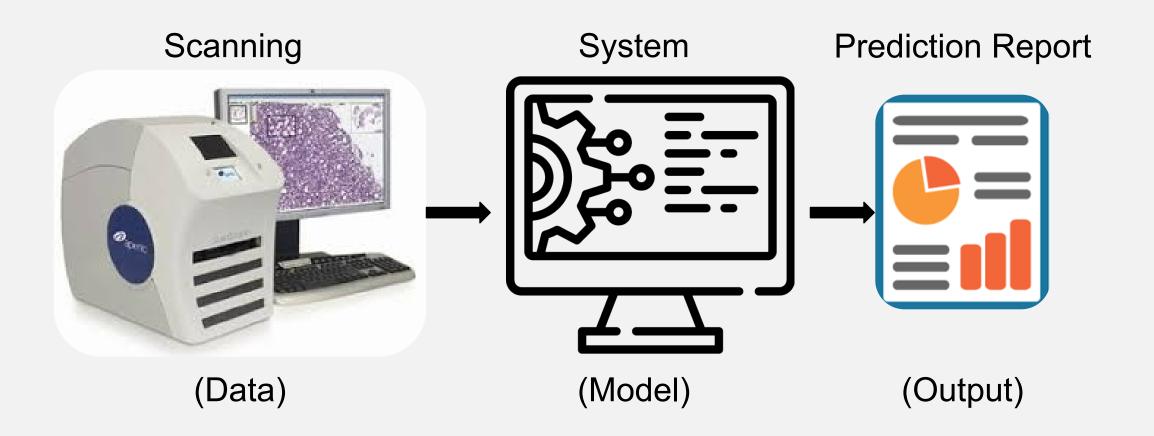
Carcinogenic-Signs Type



Cancerous Types



OUR PRODUCT



DESIGN CRITERIA / REQUIREMENTS



Classification

Source



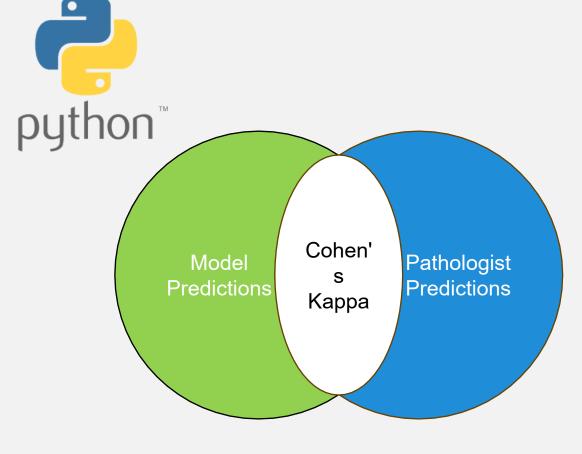


Train Time < 3 Days

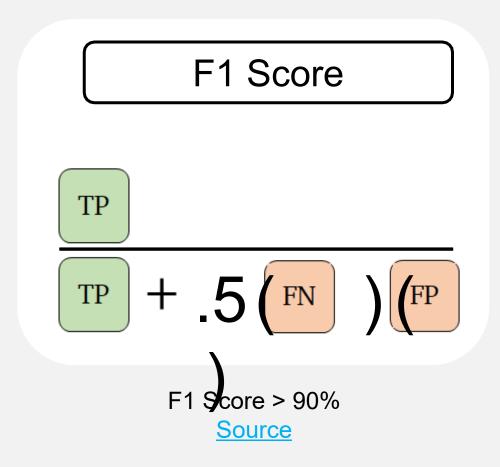
Functional GUI

- Show location of areas
- Show area's probability of malignancy

DESIGN CRITERIA / REQUIREMENTS



Cohen's Kappa > 60% Source



DEEPER LOOK AT F1 SCORE



F1 Score

TP

TP + .5 (FN) (FP)

Apples

True Positive = 4

False Negative =

Palse Positive =

f1 Score = 89%

Bananas

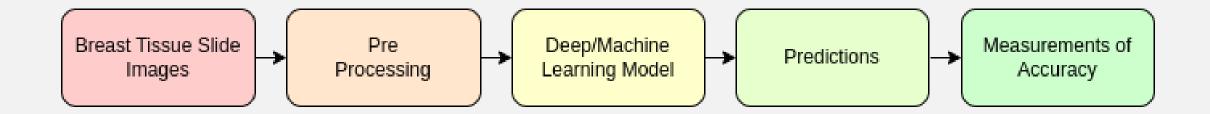
True Positive = 0

False Negative =

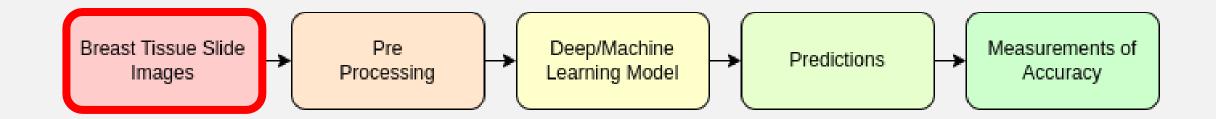
#alse Positive =

1 Score = 0%

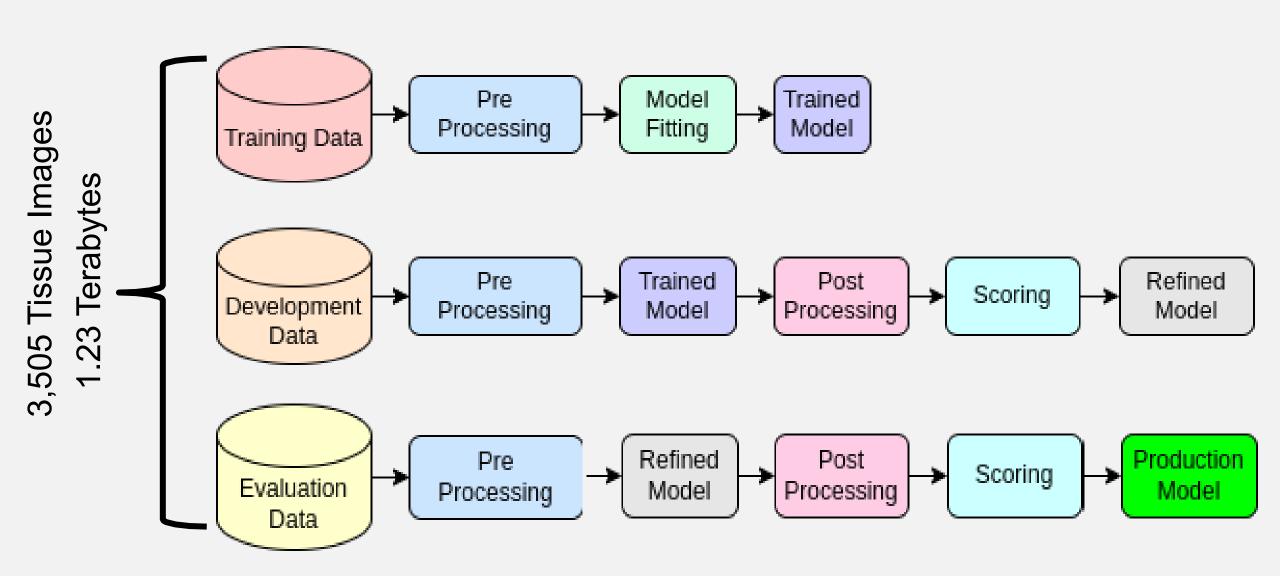
PRELIMINARY DESIGN



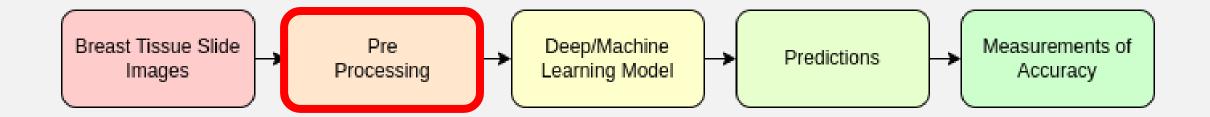
PRELIMINARY DESIGN



TRAINING, TUNING, EVALUATION PIPELINES



PRELIMINARY DESIGN



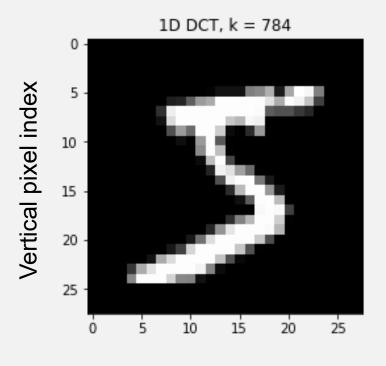
2-DIMENSIONAL DCT

 Belongs in the pre-processor stage

 Converts colors to frequencies

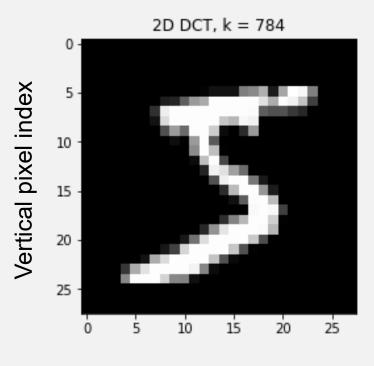
 Allows us to retain fewer features

One-dimensional DCT



Horizontal pixel index

Two-dimensional DCT



Horizontal pixel index

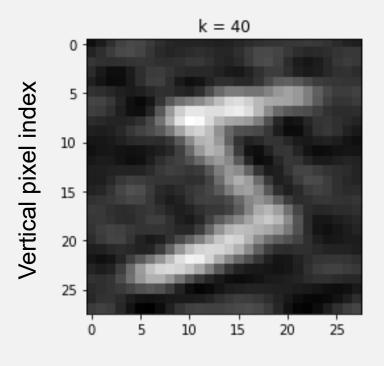
2-DIMENSIONAL DCT

 Belongs in the pre-processor stage

 Converts colors to frequencies

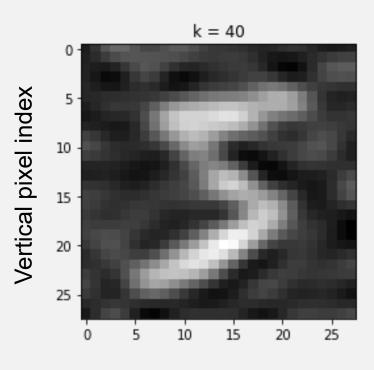
 Allows us to retain fewer features

One-dimensional DCT



Horizontal pixel index

Two-dimensional DCT



Horizontal pixel index

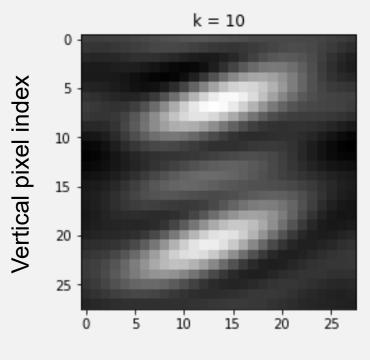
2-DIMENSIONAL DCT

 Belongs in the pre-processor stage

 Converts colors to frequencies

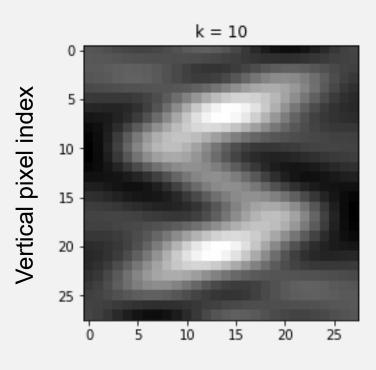
 Allows us to retain fewer features

One-dimensional DCT



Horizontal pixel index

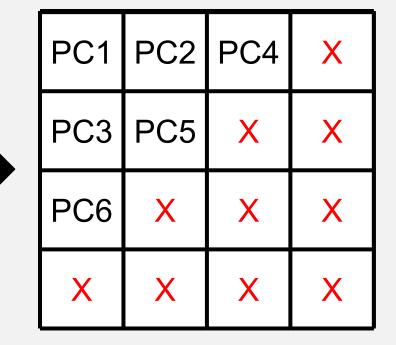
Two-dimensional DCT



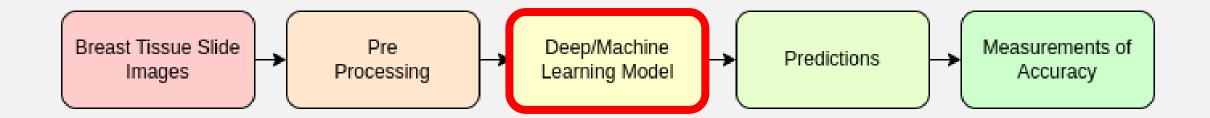
Horizontal pixel index

PRINCIPAL COMPONENT ANALYSIS (PCA)

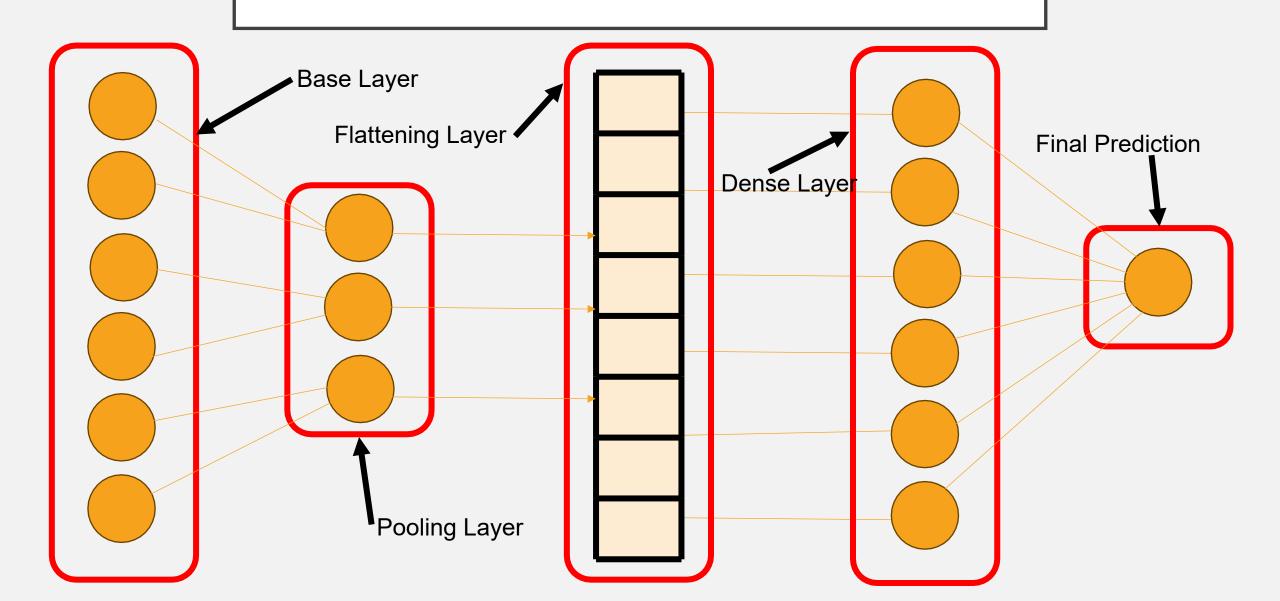
f1	f2	f4	f7
f3	f5	f8	f11
f6	f9	f12	f14
f10	f13	f15	f16



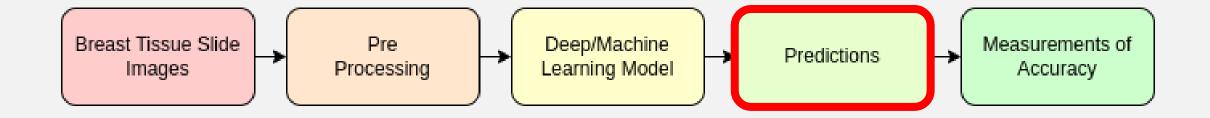
PRELIMINARY DESIGN

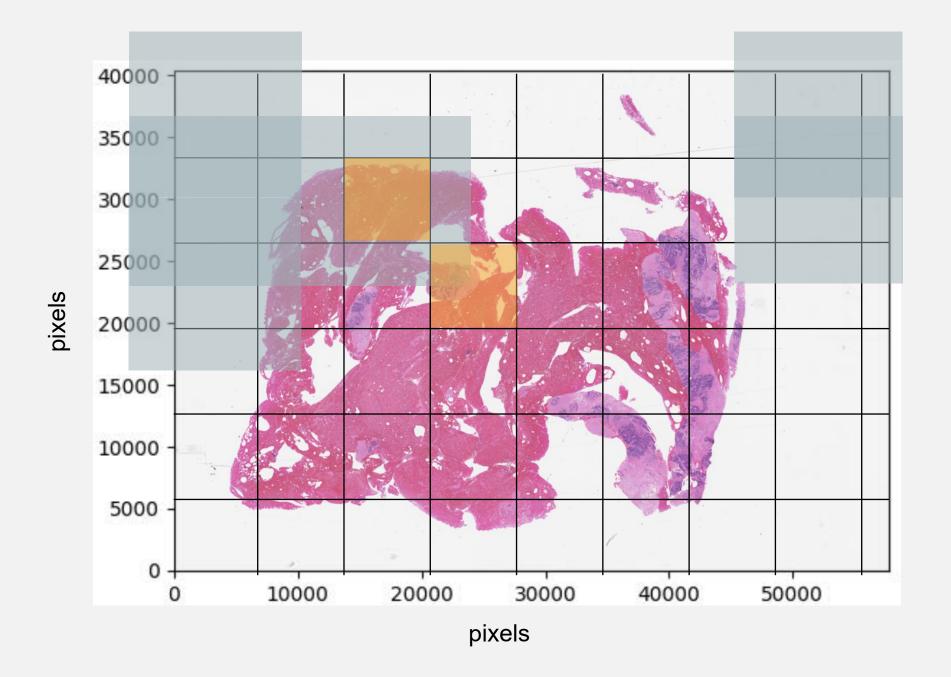


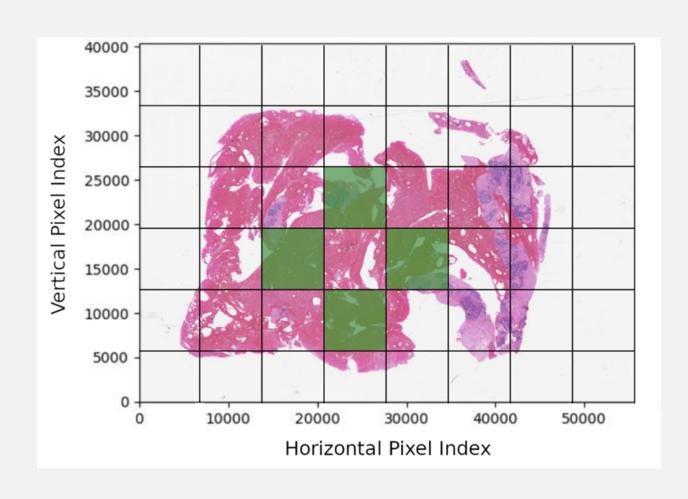
CONVOLUTIONAL NEURAL NETWORK

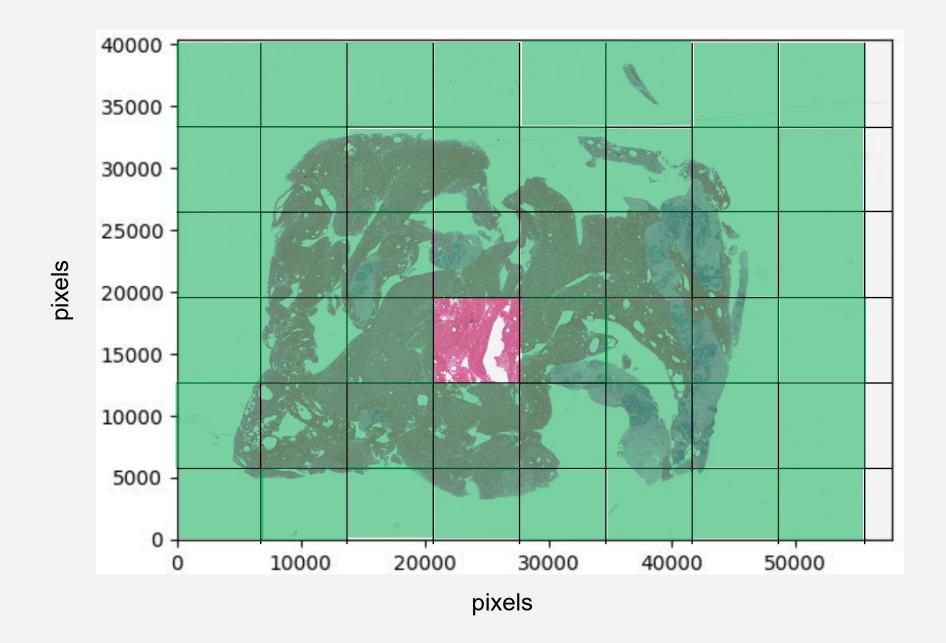


PRELIMINARY DESIGN

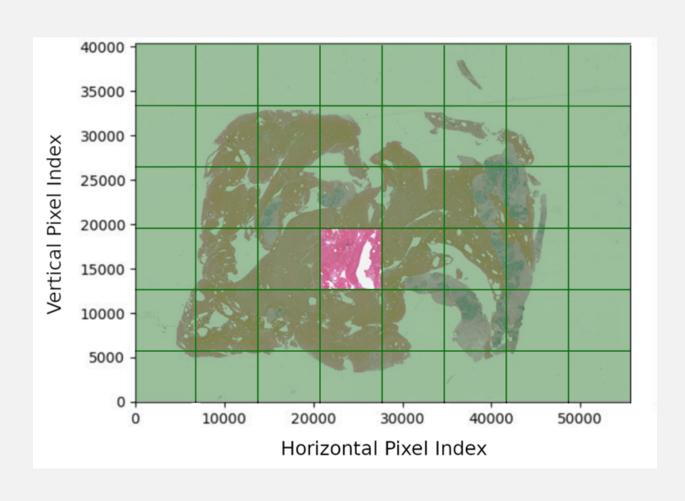


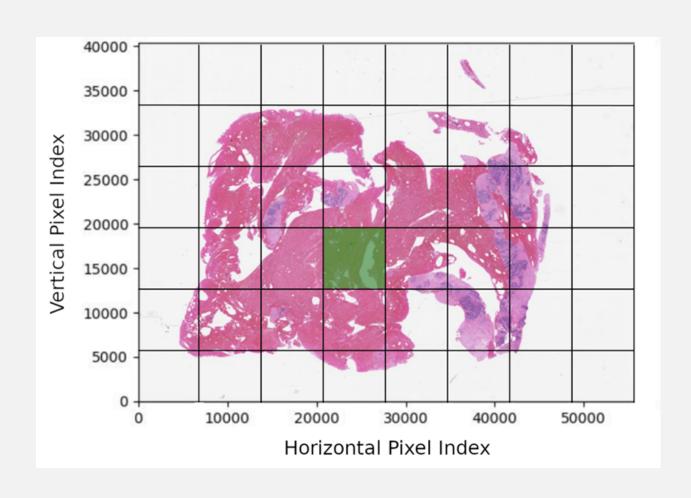


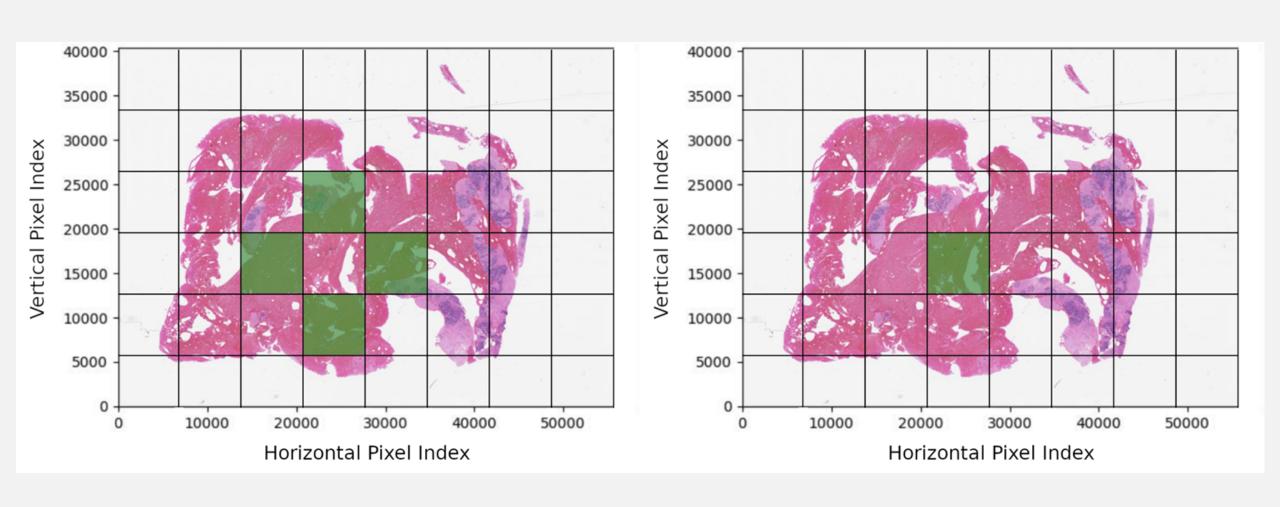


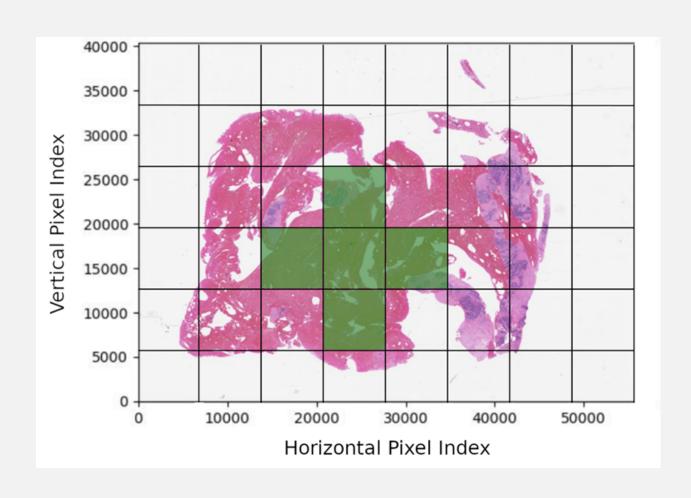


WINDOW TO PATCH



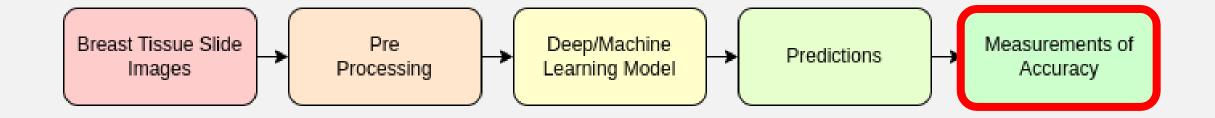






PATCH TO IMAGE LEVEL

PRELIMINARY DESIGN



FUTURE WORK

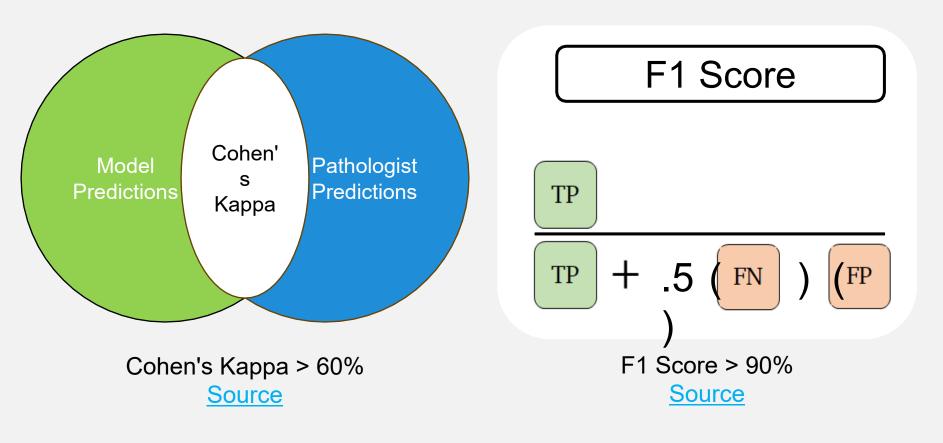


Image Classification

No Sobel/Laplacian Filters

QUESTIONS?

Acknowledgements:

Dr. Joseph Picone – Mentor & Data Coordinator Claudia Dumitrescu – Al Expert Phuykong Meng – GUI Planning & Scoring

For the curious

- <u>Benefits of Machine Learning in</u> Healthcare
- Machine Learning in Healthcare

- What is Machine Learning in Healthcare?
- <u>Significance of Machine Learning in</u> Healthcare
- <u>The Potential for Artificial Intelligence in</u> <u>Healthcare</u>

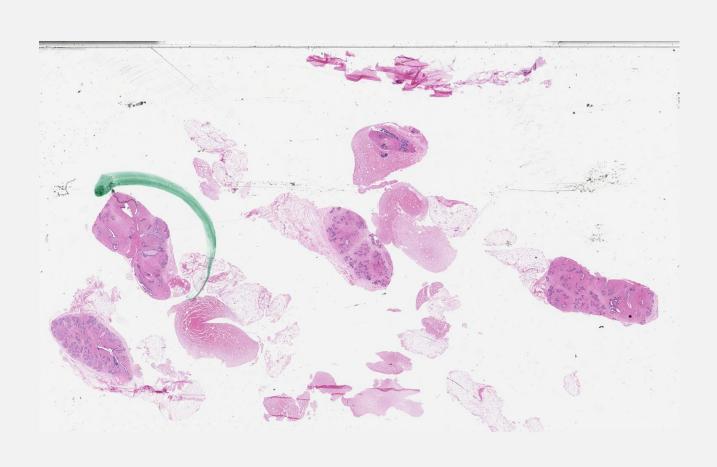
PROGRESS SINCE LAST PRESENTATION

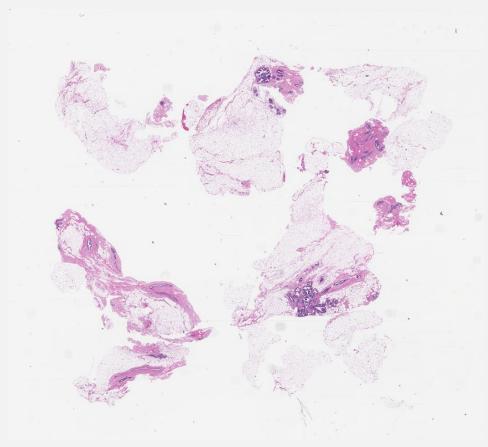
 2D Discrete Cosine Transform (DCT)

 Principal Component Analysis (PCA)

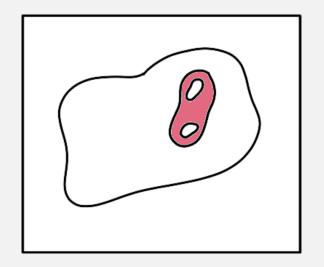
 Convolutional Neural Network (CNN)

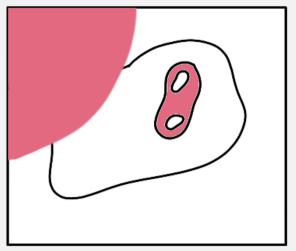
TUHDP BIOPSY SLIDE SAMPLE

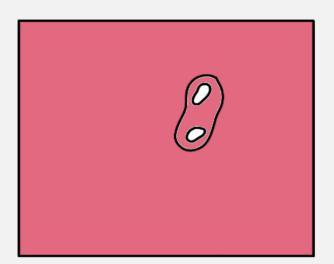


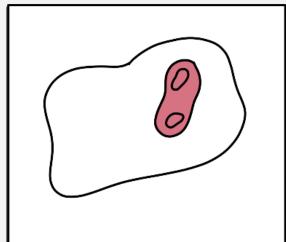


WINDOW TO PATCH

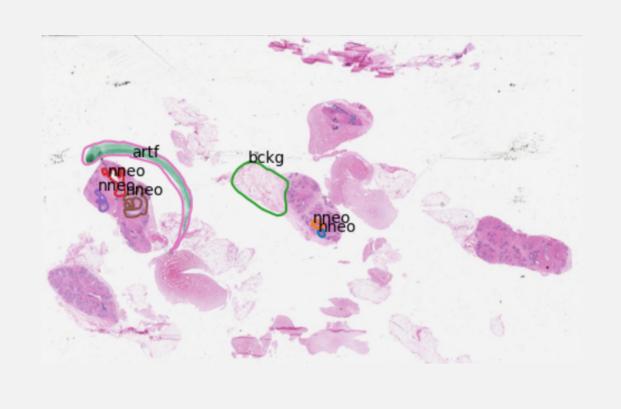






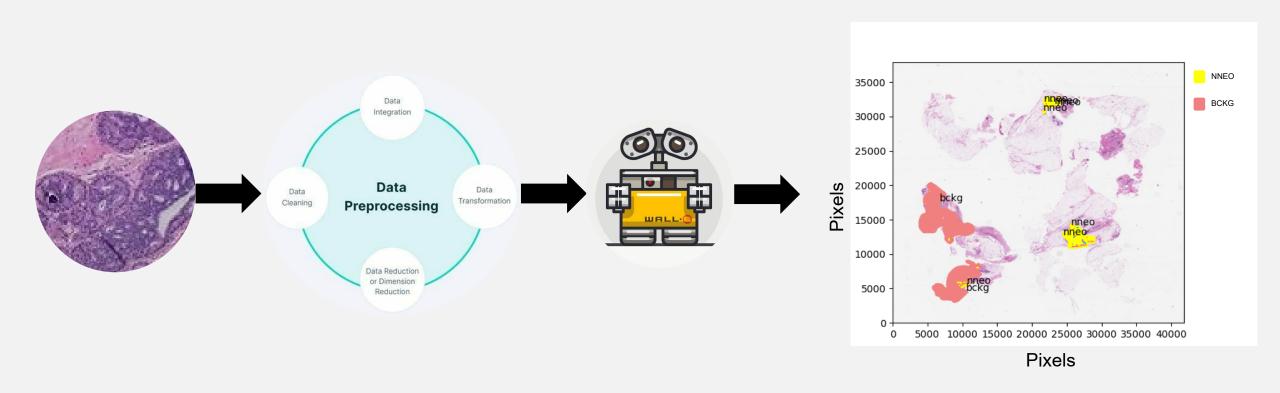


TUHDP BIOPSY SLIDE SAMPLE

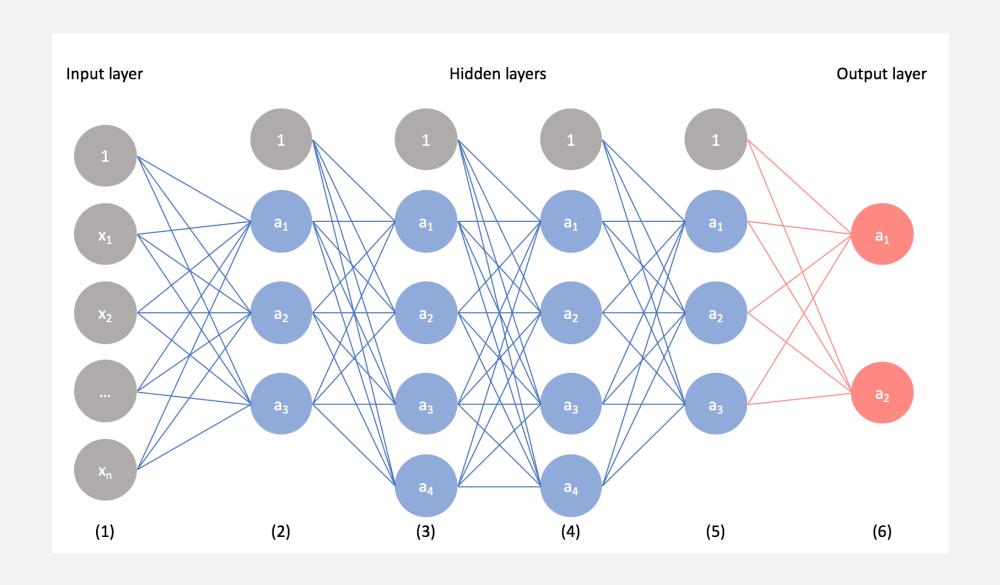




DEEPER LOOK AT MODEL I/O



CONVOLUTIONAL NEURAL NETWORK

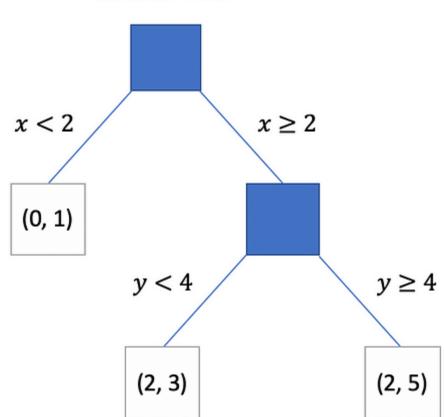


RANDOM FOREST

Dataset

х	у
0	1
2	3
2	5

Isolation Tree



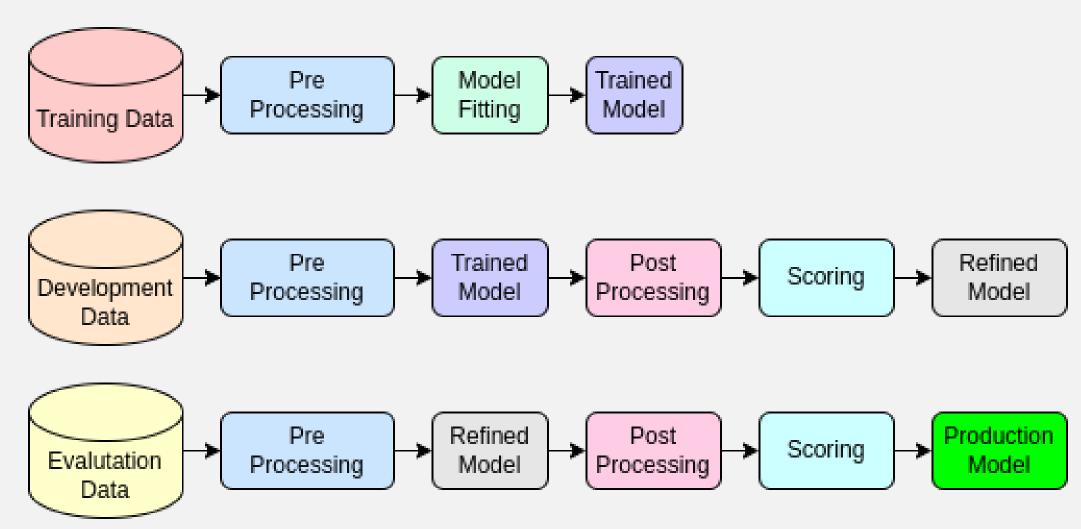
WHAT IS A MODEL?

- Three essential components for machine learning
 - Data
 - Model
 - Training algorithm
- Model
 - Mathematical representation of relationships in the data

- Training algorithm
 - Uses data
 - Adjusts variables in the model until output matches input

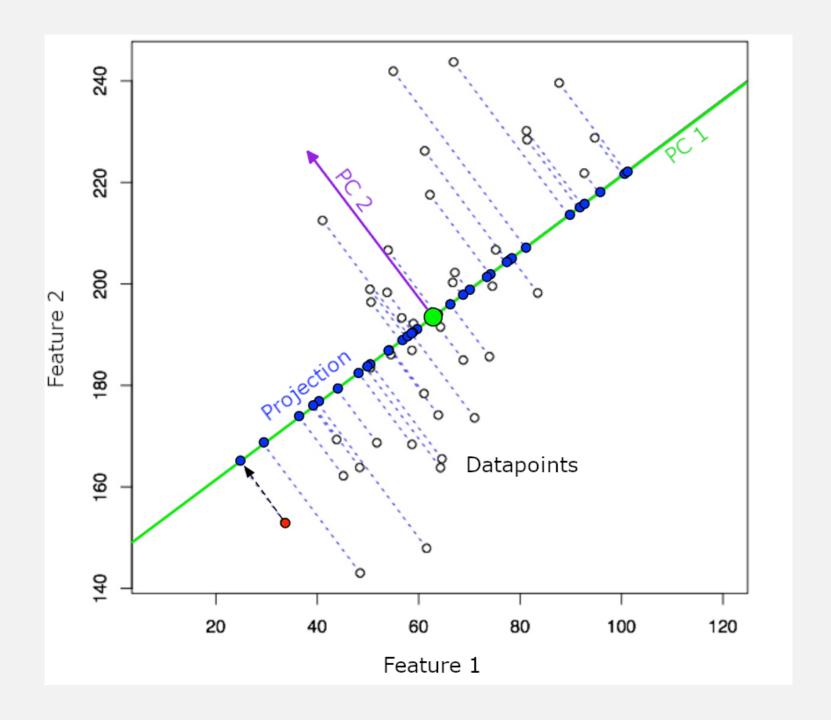
TEMPLE UNIVERSITY HEALTH DIGITAL PATHOLOGY CORPUS

3,505 Tissue Images 1.23 Terabytes



PRINCIPAL COMPONENT ANALYSIS (DIMENSION REDUCTION)

- After feature generation
- Also belongs in the pre-processor stage after digitizing/segmenting slides and before training
- Reduces the number of features while minimizing information lost from feature reduction
- Fewer features compared to no PCA or dimension reduction



TESTING GOALS

2-DIMENSIONAL DCT

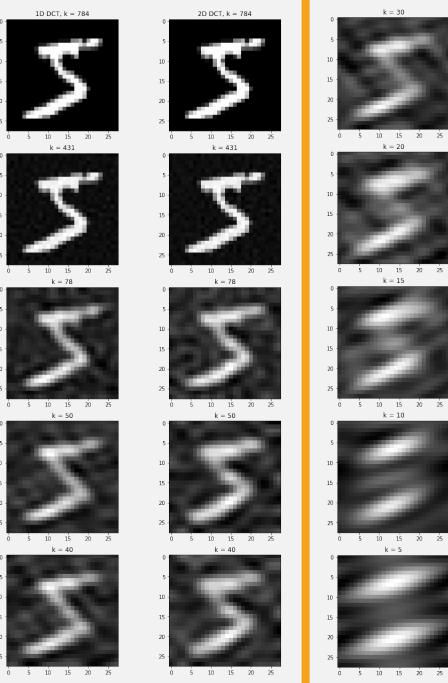
- Part of feature generation
- Belongs in the pre-processor stage after digitizing/segmenting slides and before training
- Greater spectral/energy density than onedimensional DCT
- Therefore, fewer features compared to onedimensional DCT

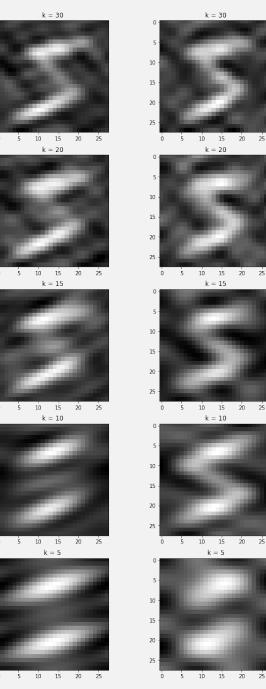
2-DIMENSIONAL DCT

 Belongs in the preprocessor stage

 Converts colors to frequencies

 Allows us to retain fewer features

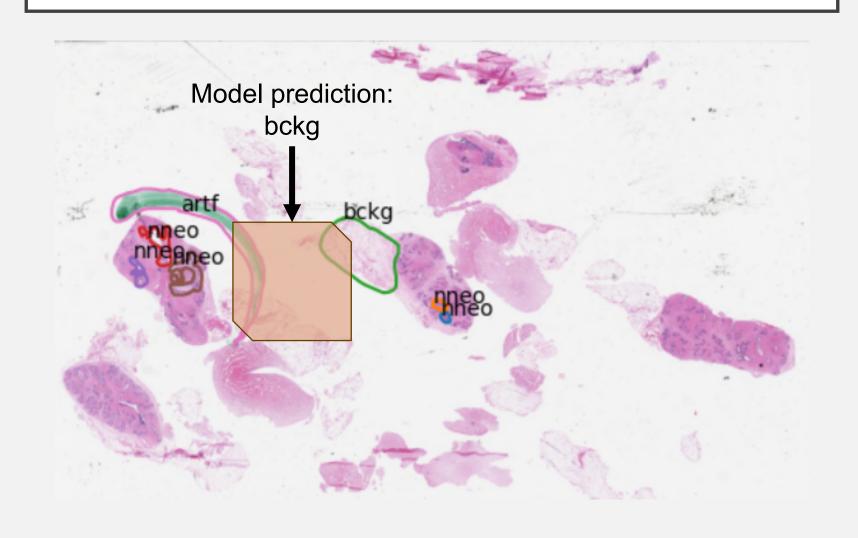




SCORING

- Find overlapping area between the model's predictions and the human pathologist's predictions
- Use overlapping area to construct a confusion matrix
- Use confusion matrix to generate F_1 scores and Cohen's kappa coefficients

OVERLAPPING AREA



Pathologist	(True
-------------	-------

	Frame Labels	Unlab	Bckg	Norm	Null	Artf	Nneo	Infl	Susp	Indc	Dcis	Sums across rows
	Unlab	20	1	4	1	7	6	7	0	4	6	56
	Bckg	6	30	1	3	5	2	4	7	3	3	64
	Norm	3	2	29	6	0	1	1	3	1	2	48
	Null	3	0	4	24	3	4	6	3	5	0	52
Model	Artf	5	6	4	7	29	3	6	2	3	3	68
(Predicted)	Nneo	1	6	6	1	3	21	5	3	3	5	54
	Infl	6	3	7	4	0	6	26	7	1	2	62
	Susp	6	4	6	4	5	3	6	22	0	6	62
	Indc	5	5	2	6	0	3	6	0	28	0	55
	Dcis	5	0	6	6	7	7	4	7	5	24	71
	Sums across columns	60	57	69	62	59	56	71	54	53	51	592

Model
(Predicted

Pathologist (True)						
	Frame Labels	NNeo	Not NNeo	Sums across		
	Tranio Edboto		110111100	rows		
	NNeo	21	33	TP+FP = 54		
	Not NNeo	35	503	FN+TN = 538		
	Sums across columns	TP+FN = 56	FP+TN = 536	592		

FILTERS



Original image



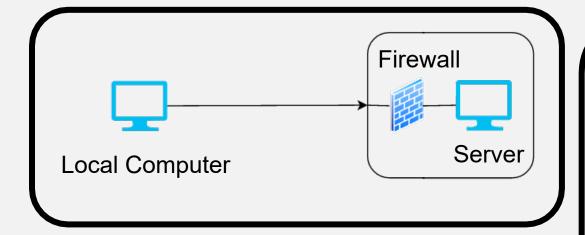
Filter "Laplace" applied

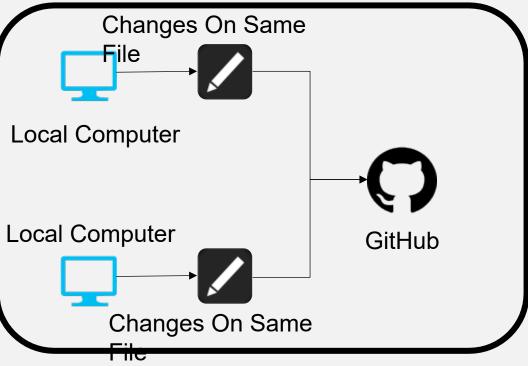
FRAME LEVEL EVALUATION RESULTS

	Dataset	Accuracy Rate [%]
	TRAIN	100.00
Random Forest	DEV	86.33
	EVAL	85.87

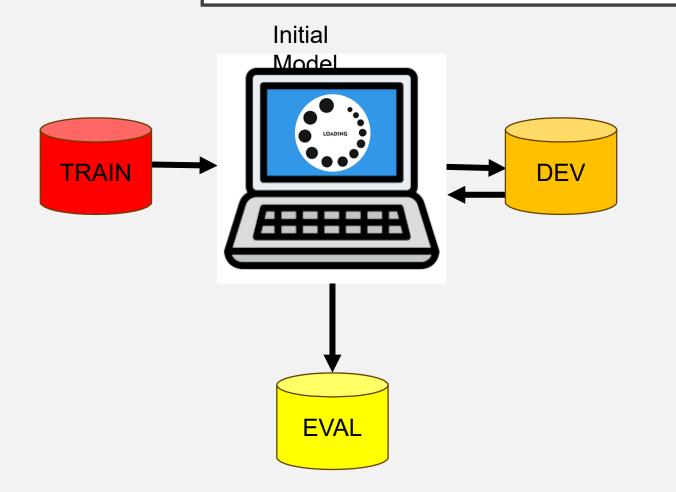
GITHUB AND THE SERVER

The Server GitHub





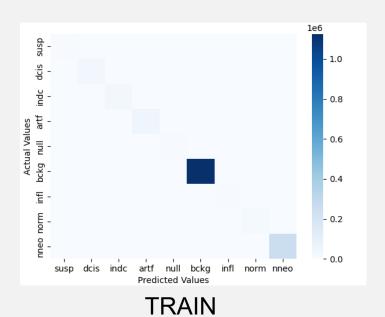
EXPLAIN TRAIN, DEV, AND EVAL IN THE PROCESS

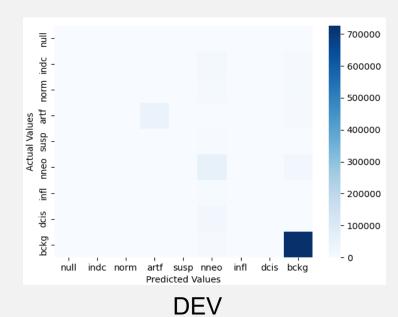


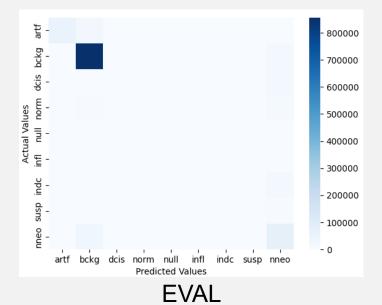


Final Model

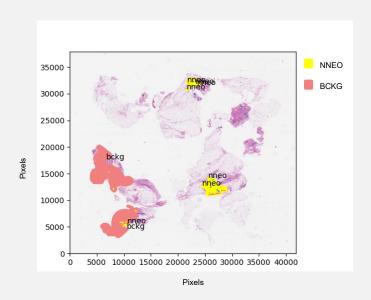
RNF CONFUSION MATRIX







RNF DECISION SURFACES



HOW THIS FITS

