بسم الله الرحمن الرحیم

CLIPath

Clip for multimodal model based on WSI image and report

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Natural Language Processing course
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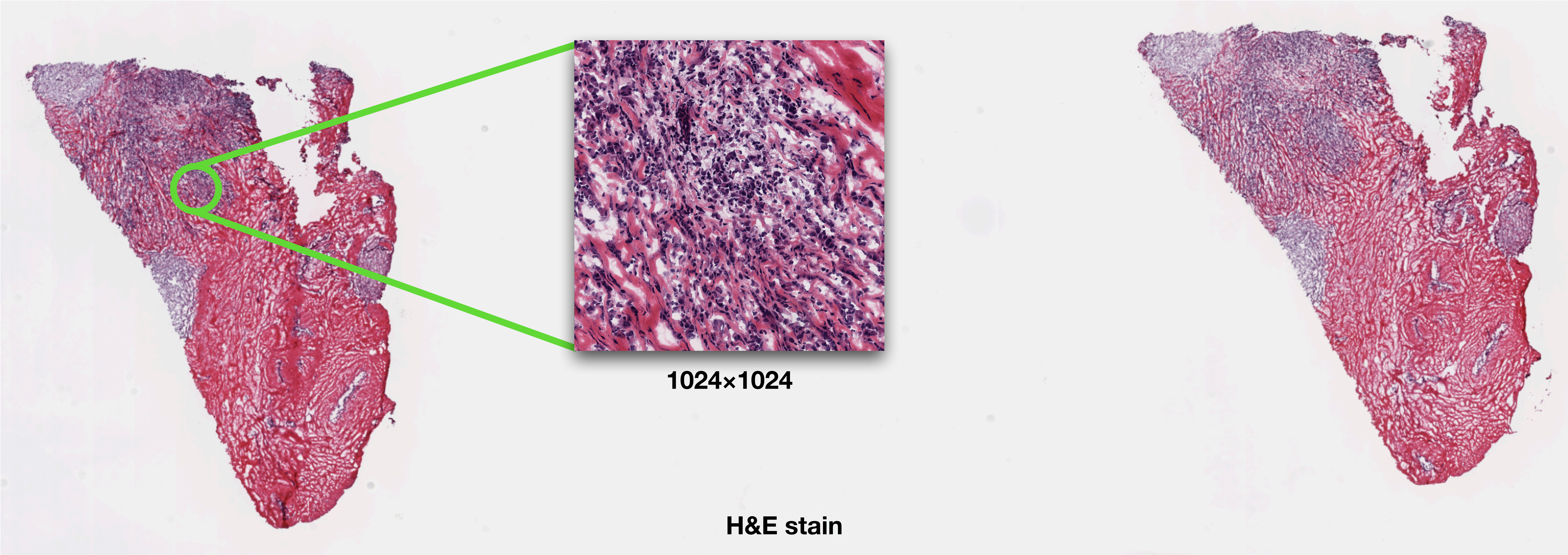
Introduction

WSI (Whole Slide Image)



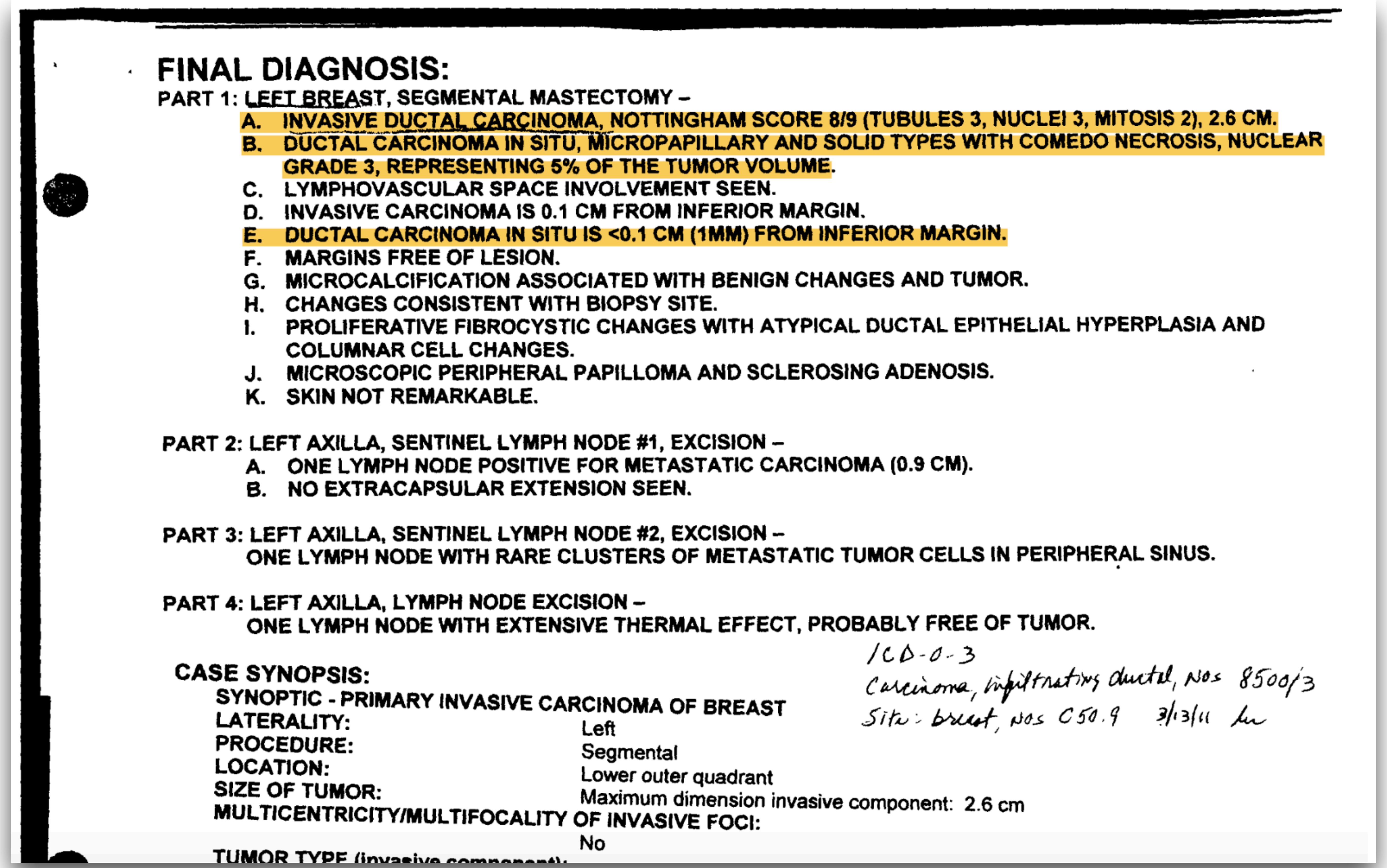
100K×40K

TCGA dataset [1]

Patch selection

TCGA dataset [1]

Reports



FINAL DIAGNOSIS:

PART 1: LEFT BREAST, SEGMENTAL MASTECTOMY –

A. INVASIVE DUCTAL CARCINOMA, NOTTINGHAM SCORE 8/9 (TUBULES 3, NUCLEI 3, MITOSIS 2), 2.6 CM.
B. DUCTAL CARCINOMA IN SITU, MICROPAPILLARY AND SOLID TYPES WITH COMEDO NECROSIS, NUCLEAR GRADE 3, REPRESENTING 5% OF THE TUMOR VOLUME.
C. LYMPHOVASCULAR SPACE INVOLVEMENT SEEN.
D. INVASIVE CARCINOMA IS 0.1 CM FROM INFERIOR MARGIN.
E. DUCTAL CARCINOMA IN SITU IS <0.1 CM (1MM) FROM INFERIOR MARGIN.
F. MARGINS FREE OF LESION.
G. MICROCALCIFICATION ASSOCIATED WITH BENIGN CHANGES AND TUMOR.
H. CHANGES CONSISTENT WITH BIOPSY SITE.
I. PROLIFERATIVE FIBROCYSTIC CHANGES WITH ATYPICAL DUCTAL EPITHELIAL HYPERPLASIA AND COLUMNAR CELL CHANGES.
J. MICROSCOPIC PERIPHERAL PAPILLOMA AND SCLEROSING ADENOSIS.
K. SKIN NOT REMARKABLE.

PART 2: LEFT AXILLA, SENTINEL LYMPH NODE #1, EXCISION –

A. ONE LYMPH NODE POSITIVE FOR METASTATIC CARCINOMA (0.9 CM).
B. NO EXTRACAPSULAR EXTENSION SEEN.

PART 3: LEFT AXILLA, SENTINEL LYMPH NODE #2, EXCISION –

ONE LYMPH NODE WITH RARE CLUSTERS OF METASTATIC TUMOR CELLS IN PERIPHERAL SINUS.

PART 4: LEFT AXILLA, LYMPH NODE EXCISION –

ONE LYMPH NODE WITH EXTENSIVE THERMAL EFFECT, PROBABLY FREE OF TUMOR.

ICD-O-3
Carcinoma, infiltrating ductal, NOS 8500/3
Site: breast, NOS C50.9 3/13/11

CASE SYNOPSIS:

SYNOPTIC - PRIMARY INVASIVE CARCINOMA OF BREAST

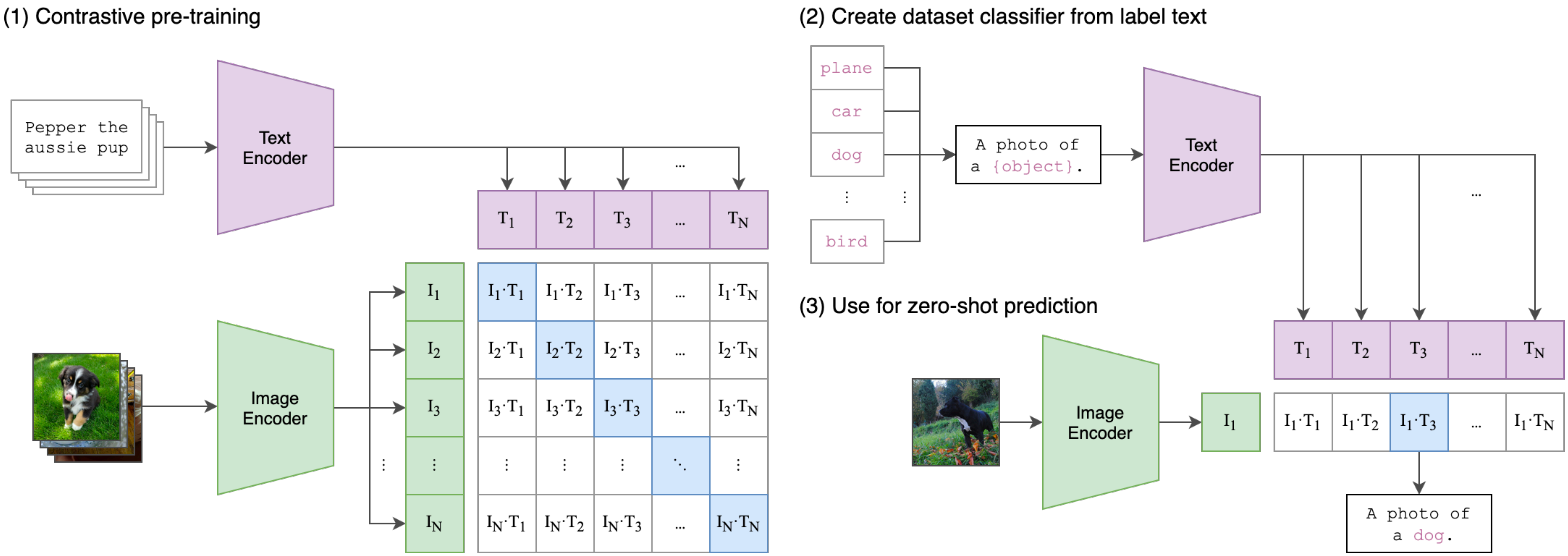
LATERALITY:	Left
PROCEDURE:	Segmental
LOCATION:	Lower outer quadrant
SIZE OF TUMOR:	Maximum dimension invasive component: 2.6 cm
MULTICENTRICITY/MULTIFOCALITY OF INVASIVE FOCI:	No

TUMOR TYPE (invasive component):

INVASIVE DUCTAL CARCINOMA, DUCTAL CARCINOMA IN SITU, MICROPAPILLARY AND SOLID TYPES WITH COMEDO NECROSIS. DUCTAL CARCINOMA IN SITU IS NEAR INFERIOR MARGIN.

TCGA dataset [1]

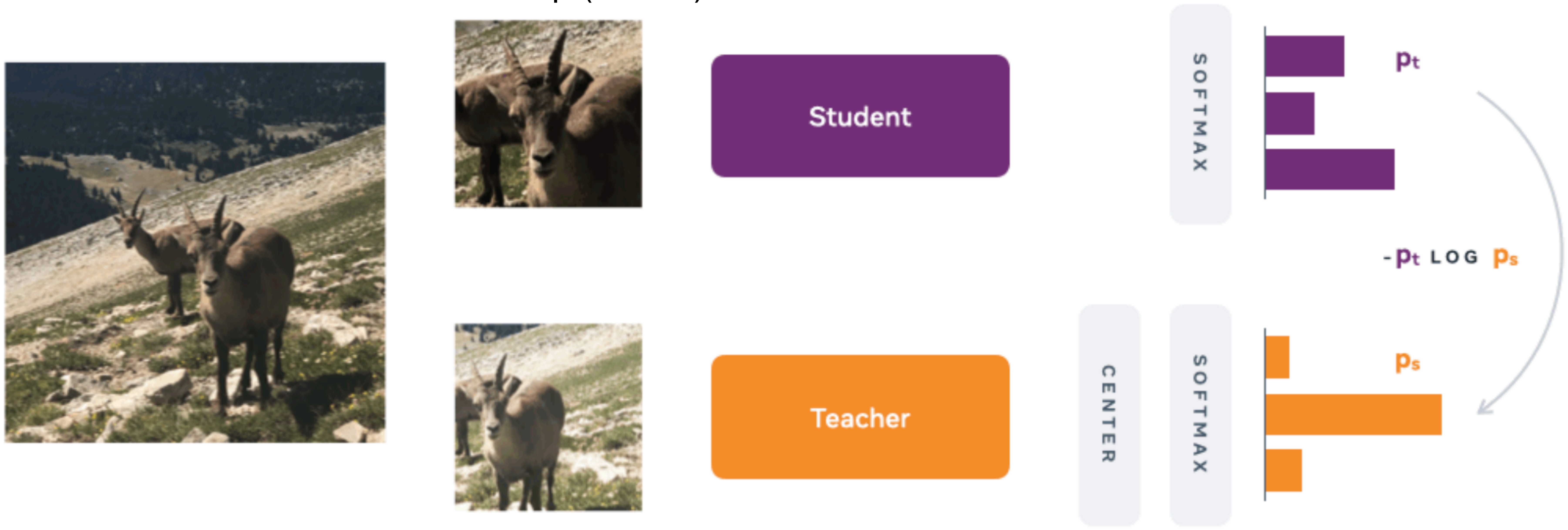
CLIP



Learning transferable visual models from natural language supervision (CLIP) [2]

DINO

Global Crop (> 50%)
&
Local Crop (< 50%)

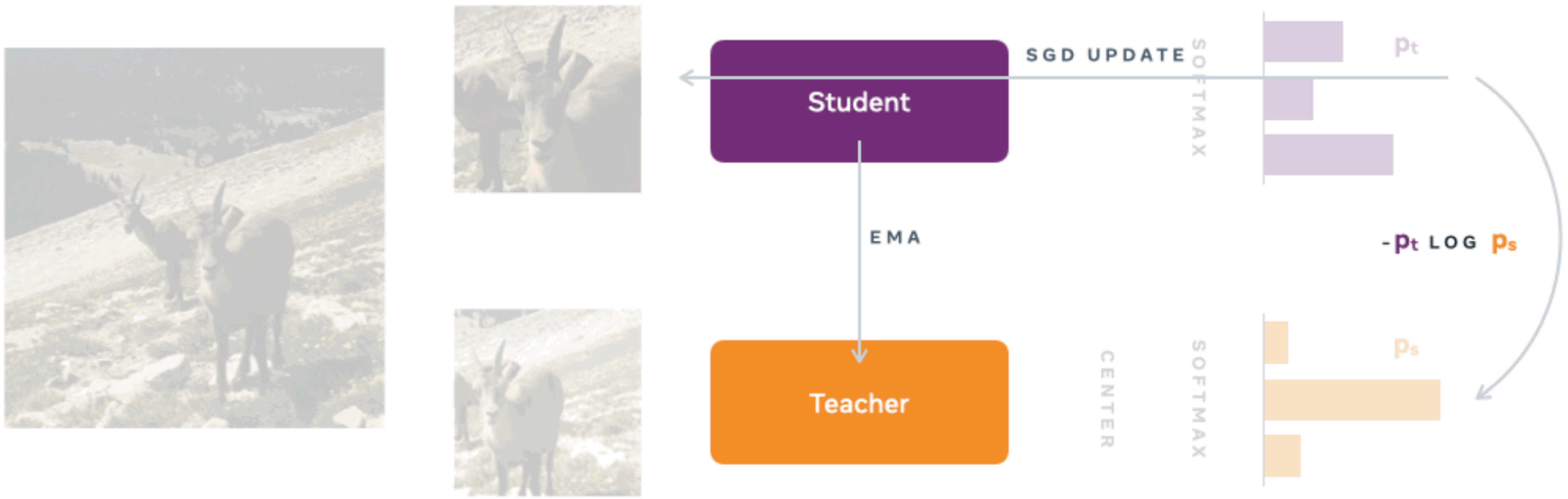


Global Crop (> 50%)

The average embedding subtracts the rest from this sample by a very small factor

Emerging properties in self-supervised vision transformers (DINO) [3]

DINO



Emerging properties in self-supervised vision transformers (DINO) [3]

Pathology BERT

PathologyBERT - Pre-trained Vs. A New Transformer Language Model for Pathology Domain

Thiago Santos, MS[1], Amara Tariq, Ph.D.[2], Susmita Das, MS[3], Kavyasree Vayalpati, MS[4], Geoffrey H. Smith, MD[5], Hari Trivedi, MD[6], Imon Banerjee, Ph.D[2,4]

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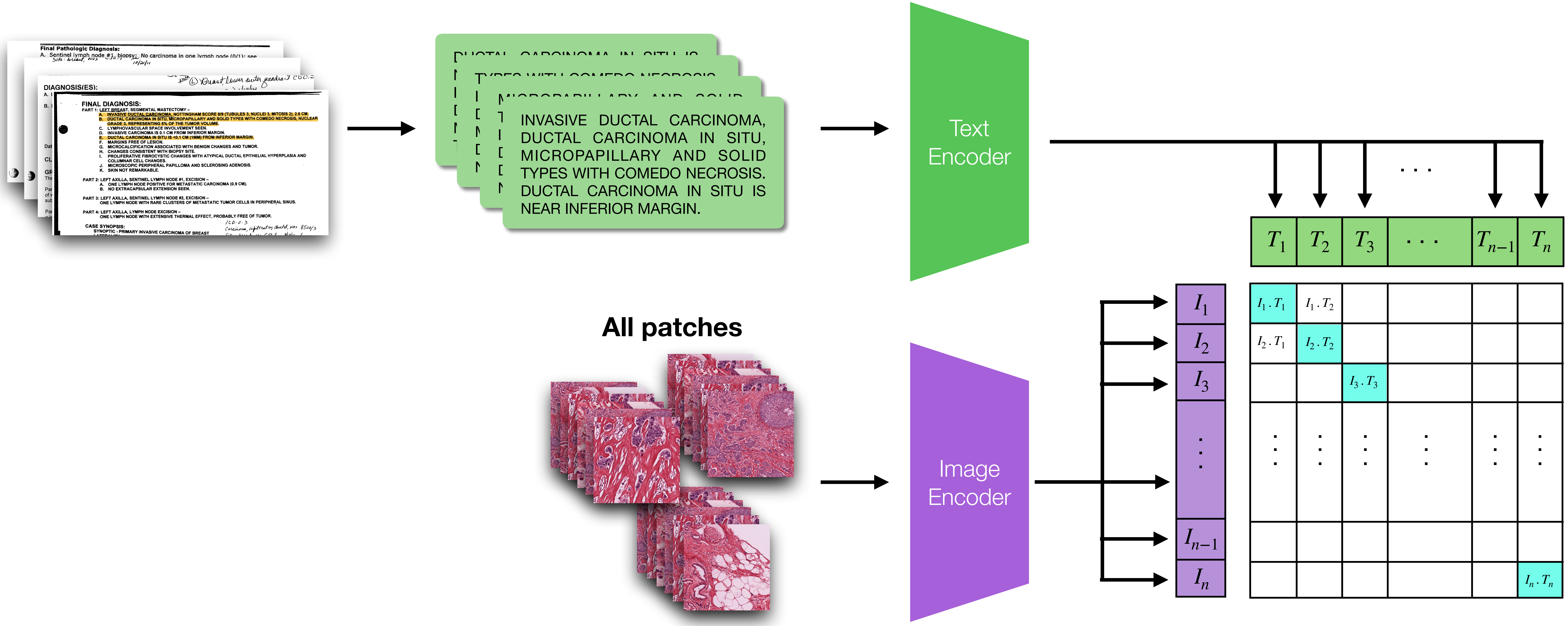
Abstract *Pathology text mining is a challenging task given the reporting variability and constant new findings in cancer sub-type definitions. However, successful text mining of a large pathology database can play a critical role to advance 'big data' cancer research like similarity-based treatment selection, case identification, prognostication, surveillance, clinical trial screening, risk stratification, and many others. While there is a growing interest in developing language models for more specific clinical domains, no pathology-specific language space exist to support the rapid data-mining development in pathology space. In literature, a few approaches fine-tuned general transformer models on specialized corpora while maintaining the original tokenizer, but in fields requiring specialized terminology, these models often fail to perform adequately. We propose PathologyBERT - a pre-trained masked language model which was trained on 347,173 histopathology specimen reports and publicly released in the Huggingface[1]repository. Our comprehensive experiments demonstrate that pre-training of transformer model on pathology corpora yields performance improvements on Natural Language Understanding (NLU) and Breast Cancer Diagnose Classification when compared to nonspecific language models.*

Change Tokenizer

A bert model generates diagnostically relevant semantic embeddings from pathology synopses with active learning (PathologyBERT) [4]

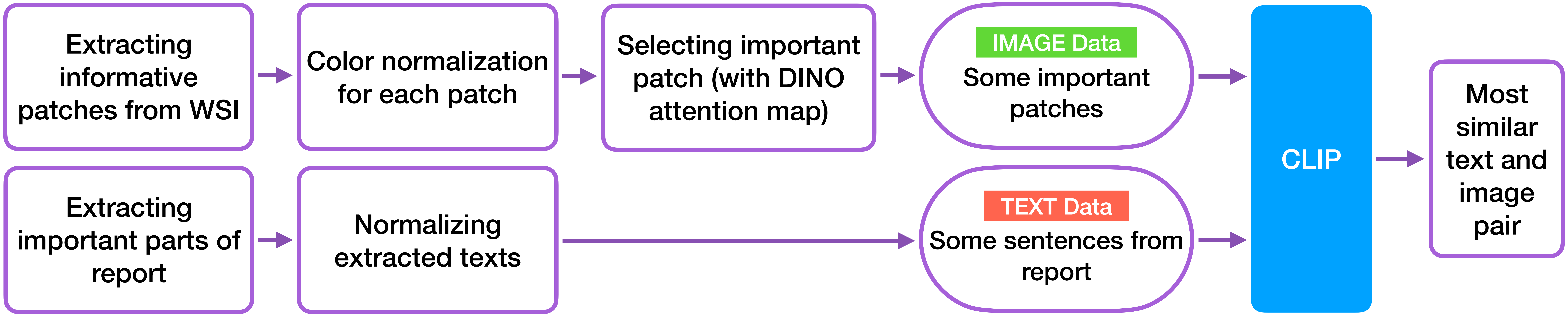
Baseline

Baseline model



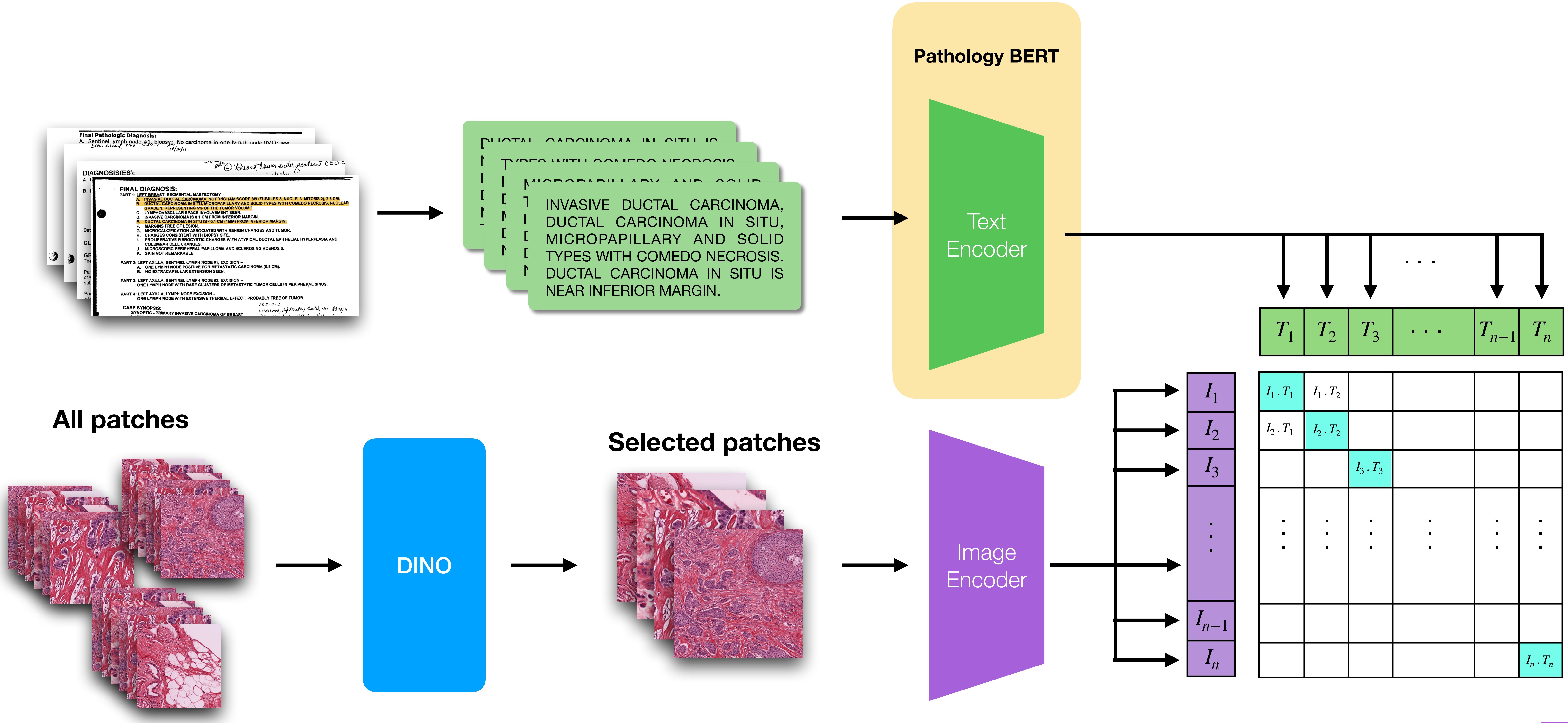
Proposed Model

Pipeline



Extracting informative patches from WSI
Color normalization for each patch
Selecting important patch (with DINO attention map)
IMAGE Data
Some important patches
Extracting important parts of report
Normalizing extracted texts
TEXT Data
Some sentences from report
CLIP
Most similar text and image pair

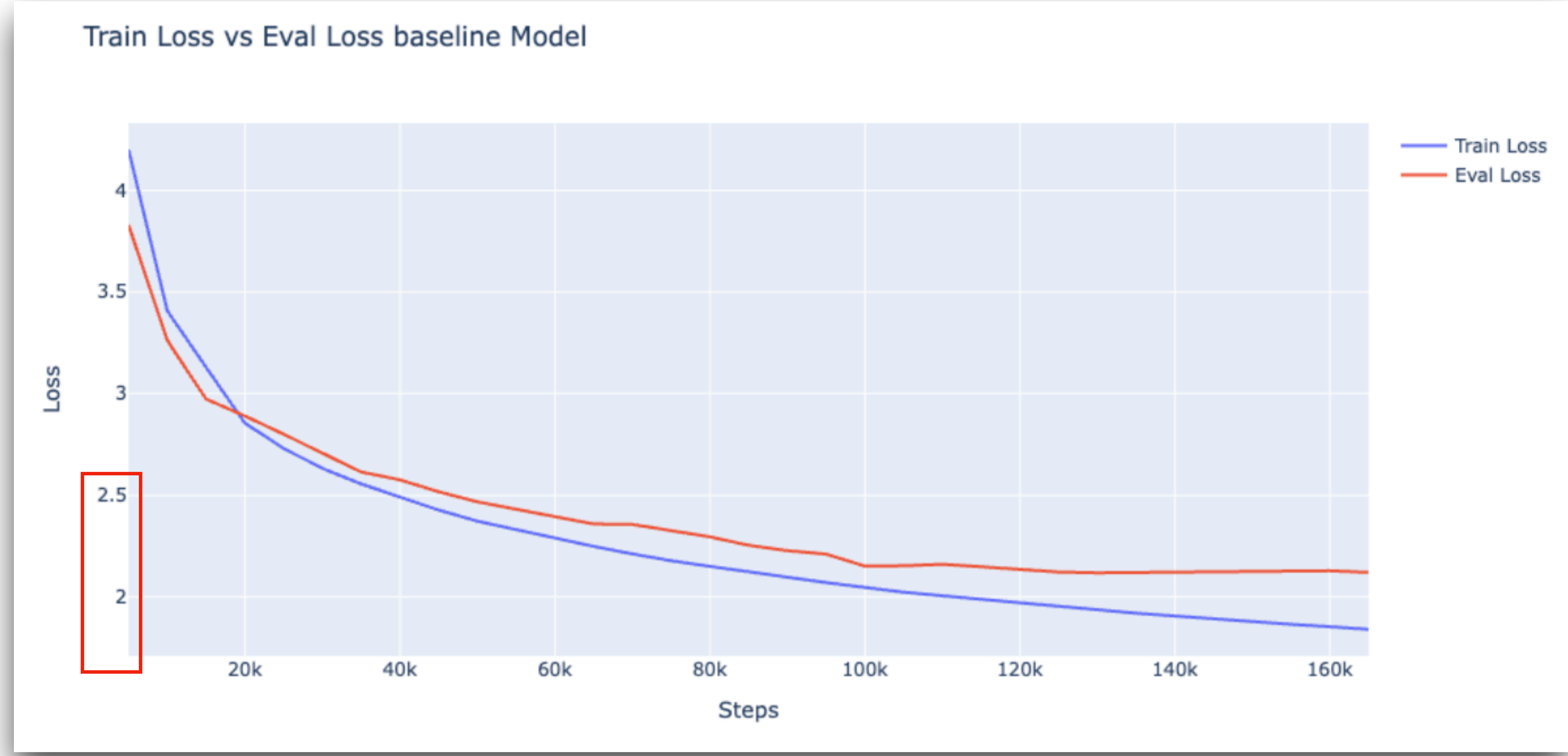
CLIPath



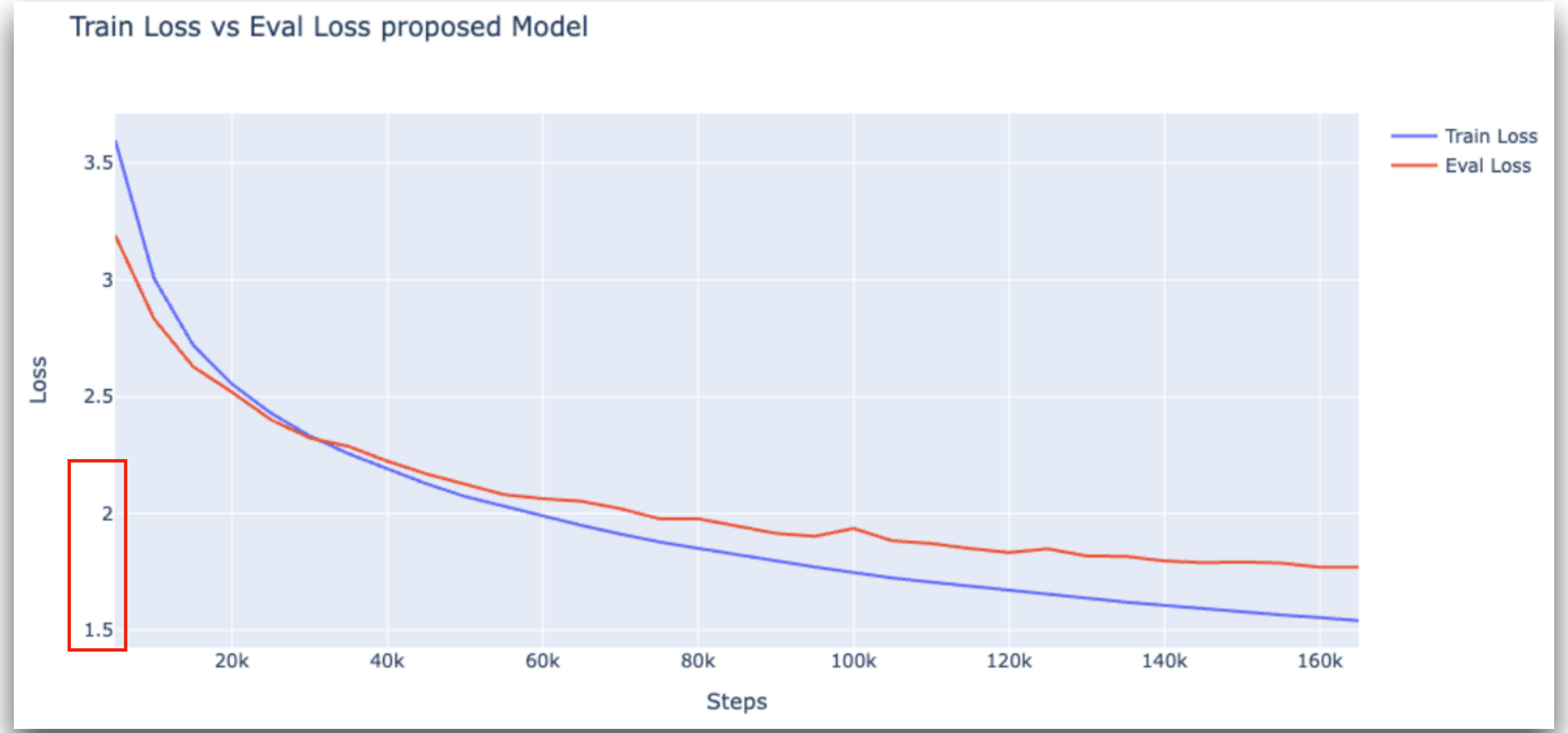
Pathology BERT
Text
Encoder
INVASIVE DUCTAL CARCINOMA, DUCTAL CARCINOMA IN SITU, MICROPAPILLARY AND SOLID TYPES WITH COMEDO NECROSIS. DUCTAL CARCINOMA IN SITU IS NEAR INFERIOR MARGIN.
All patches
DINO
Selected patches
Image
Encoder
T_1 T_2 T_3 ... T_{n-1} T_n
I_1 I_2 I_3 ... I_{n-1} I_n
$I_1 \cdot T_1$ $I_1 \cdot T_2$
$I_2 \cdot T_1$ $I_2 \cdot T_2$
$I_3 \cdot T_3$
$I_n \cdot T_n$

Results

Results



Train Loss vs Eval Loss baseline Model
Train Loss
Eval Loss
Loss
4
3.5
3
2.5
2
20k
40k
60k
80k
100k
120k
140k
160k
Steps

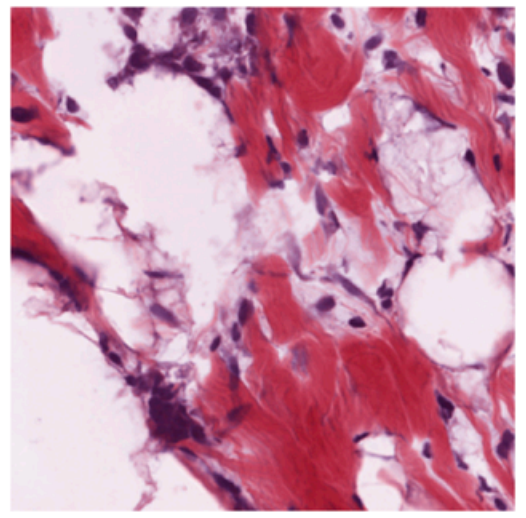


Train Loss vs Eval Loss proposed Model
Train Loss
Eval Loss
Loss
3.5
3
2.5
2
1.5
20k
40k
60k
80k
100k
120k
140k
160k
Steps

Results

	Baseline model	**CLIPath model**
Accuracy	0.525	0.698
Top-5 Accuracy	0.57	0.72

Results

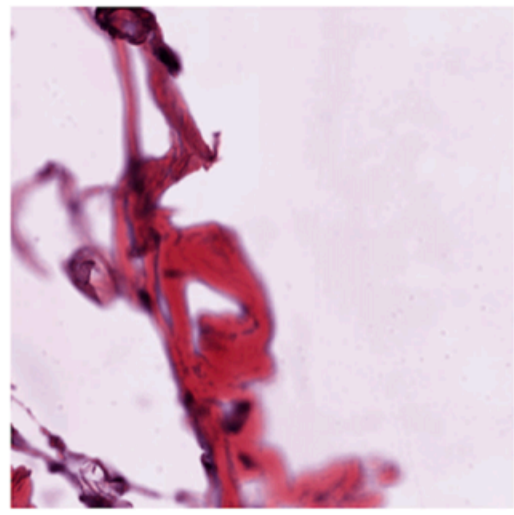


Baseline

38%	ivasive ductal carcinoma, ducal carcinoma in situ
36%	invasive ductal carcinoma with lobular features.
25%	invasive lobular carcinoma in greatest linear dimension.

CLIPath

53%	invasive ductal carcinoma with lobular features.
26%	ivasive ductal carcinoma, ducal carcinoma in situ
21%	invasive lobular carcinoma in greatest linear dimension.



Baseline

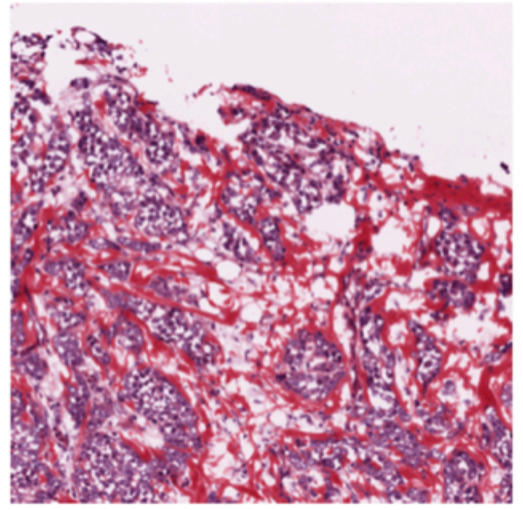
46%	infiltrating ducal carcinoma.
27%	ivasive ductal carcinoma, ducal carcinoma in situ
27%	invasive lobular carcinoma in greatest linear dimension.

CLIPath

49%	infiltrating ducal carcinoma.
27%	ivasive ductal carcinoma, ducal carcinoma in situ
23%	invasive lobular carcinoma in greatest linear dimension.

1024×1024

Results



Baseline

57% invasive ductal carcinoma.

25% ivasive ductal carcinoma, ducal carcinoma in situ

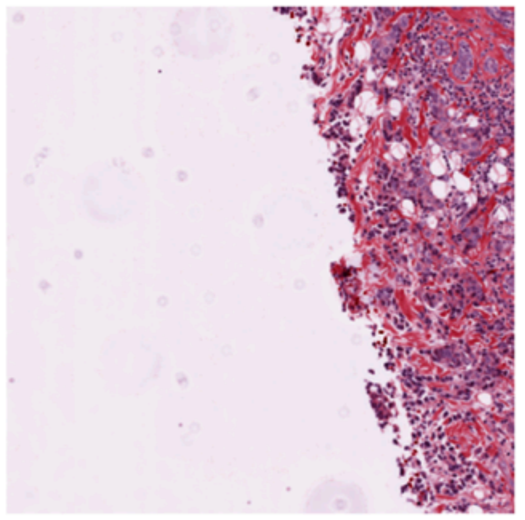
18% invasive lobular carcinoma in greatest linear dimension.

CLIPath

47% invasive ductal carcinoma.

28% ivasive ductal carcinoma, ducal carcinoma in situ

25% invasive lobular carcinoma in greatest linear dimension.



Baseline

48% invasive ductal carcinoma.

31% invasive lobular carcinoma in greatest linear dimension.

21% ivasive ductal carcinoma, ducal carcinoma in situ

CLIPath

39% invasive ductal carcinoma.

33% ivasive ductal carcinoma, ducal carcinoma in situ

28% invasive lobular carcinoma in greatest linear dimension.

3072×3072

Discussion

Discussion

- We create new dataset (selected part of report and informative patch of WSI)
- Our proposed model get better Accuracy and lower Loss within all reports
- The limitation of computing resources was one of the challenges of this project, which did not allow testing better and more methods.
- There is still a lot of work to be done and it is possible to provide better solutions to improve the model.

Future works

Future works

- More effective way for first stage of patch selection
- Using other method for main model (e.g. MIL, Ava. Pool, …)
- Using creative method to select important part of report automated (e.g. MIL)
- Using more powerful computational units (e.g. GPU with more memory)

References

References

[1] National Cancer Institute 2023, The Cancer Genome Atlas Program (TCGA), accessed 9 March 2023, https://www.cancer.gov/about-nci/organization/ccg/research/structural-genomics/tcga

[2] Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., ... & Sutskever, I. (2021, July). Learning transferable visual models from natural language supervision. In *International conference on machine learning* (pp. 8748-8763). PMLR.

[3] Caron, M., Touvron, H., Misra, I., Jégou, H., Mairal, J., Bojanowski, P., & Joulin, A. (2021). Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 9650-9660).

[4] Mu, Y., Tizhoosh, H. R., Tayebi, R. M., Ross, C., Sur, M., Leber, B., & Campbell, C. J. (2021). A bert model generates diagnostically relevant semantic embeddings from pathology synopses with active learning. *Communications Medicine*, *1*(1), 11.

Thanks For
Your
Attention :)