



CLIPath

Clip for multimodal model based on WSI image and report

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Natural Language Processing course
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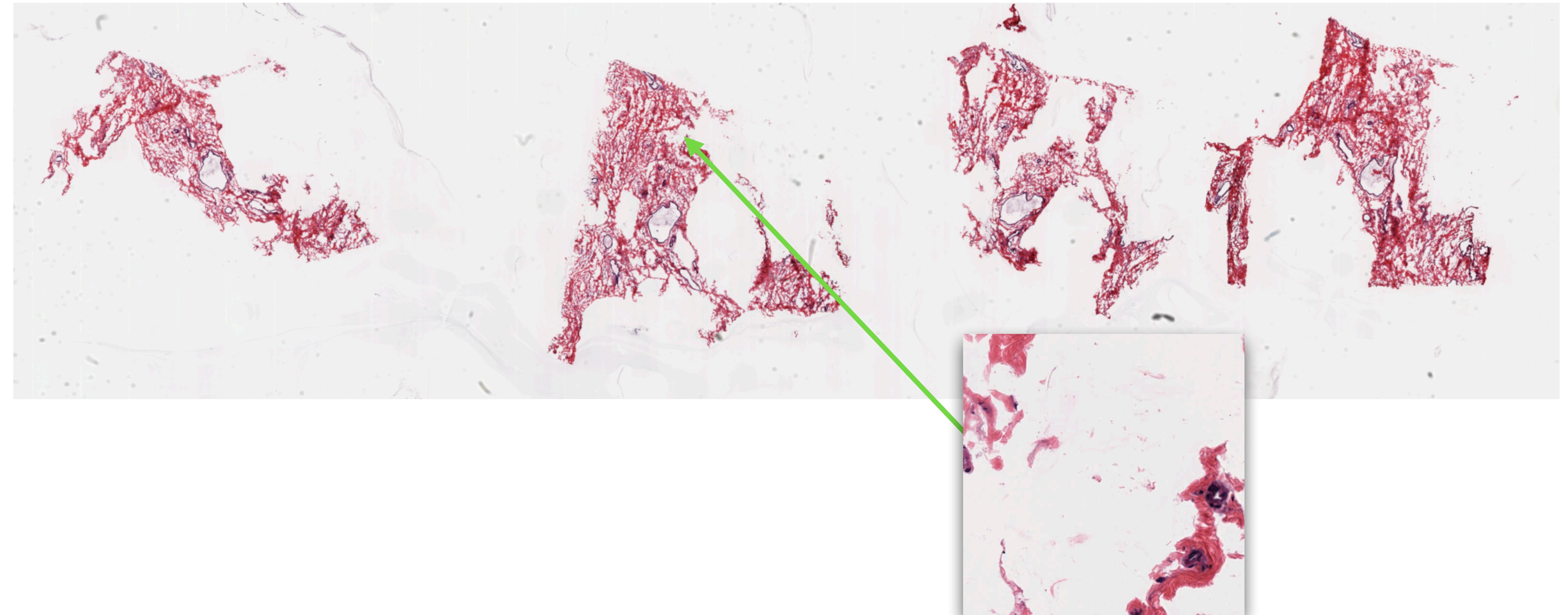
Introduction

WSI (Whole Slide Image)



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.

CASE SYNOPSIS:

SYNOPTIC - PRIMARY INVASIVE CARCINOMA OF BREAST

LATERALITY:

Left

PROCEDURE:

Segmental

LOCATION:

Lower outer quadrant

SIZE OF TUMOR:

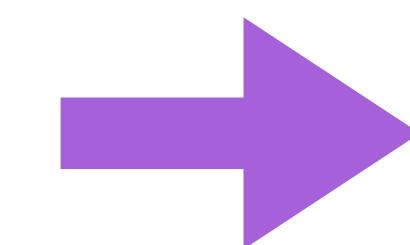
Maximum dimension invasive component: 2.6 cm

MULTICENTRICITY/MULTIFOCALITY OF INVASIVE FOCI:

No

TUMOR TYPE (Invasive component)

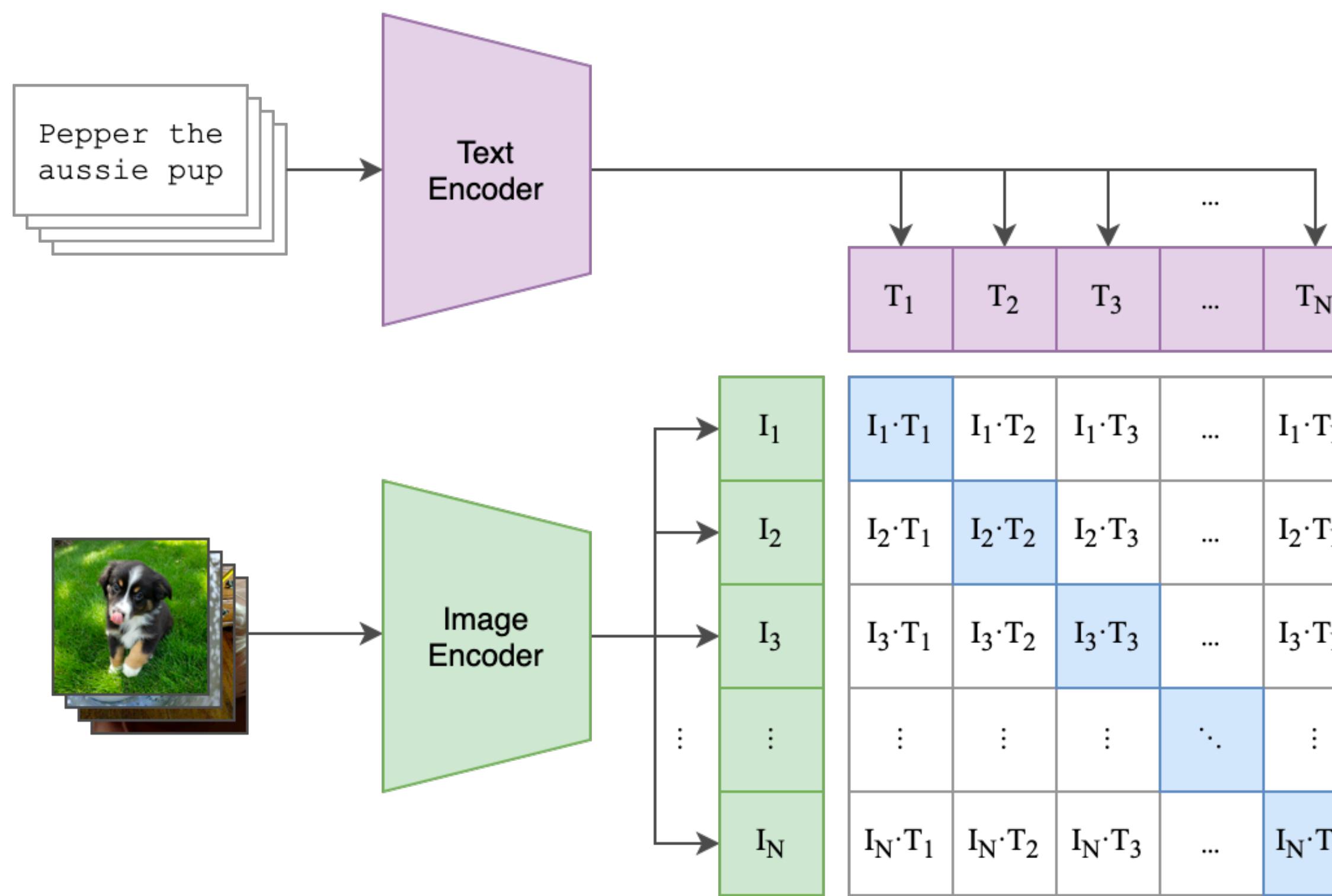
ICD-O-3
Carcinoma, infiltrating ductal, nos 8500/3
Site: breast, nos C50.9 3/3/11 hr



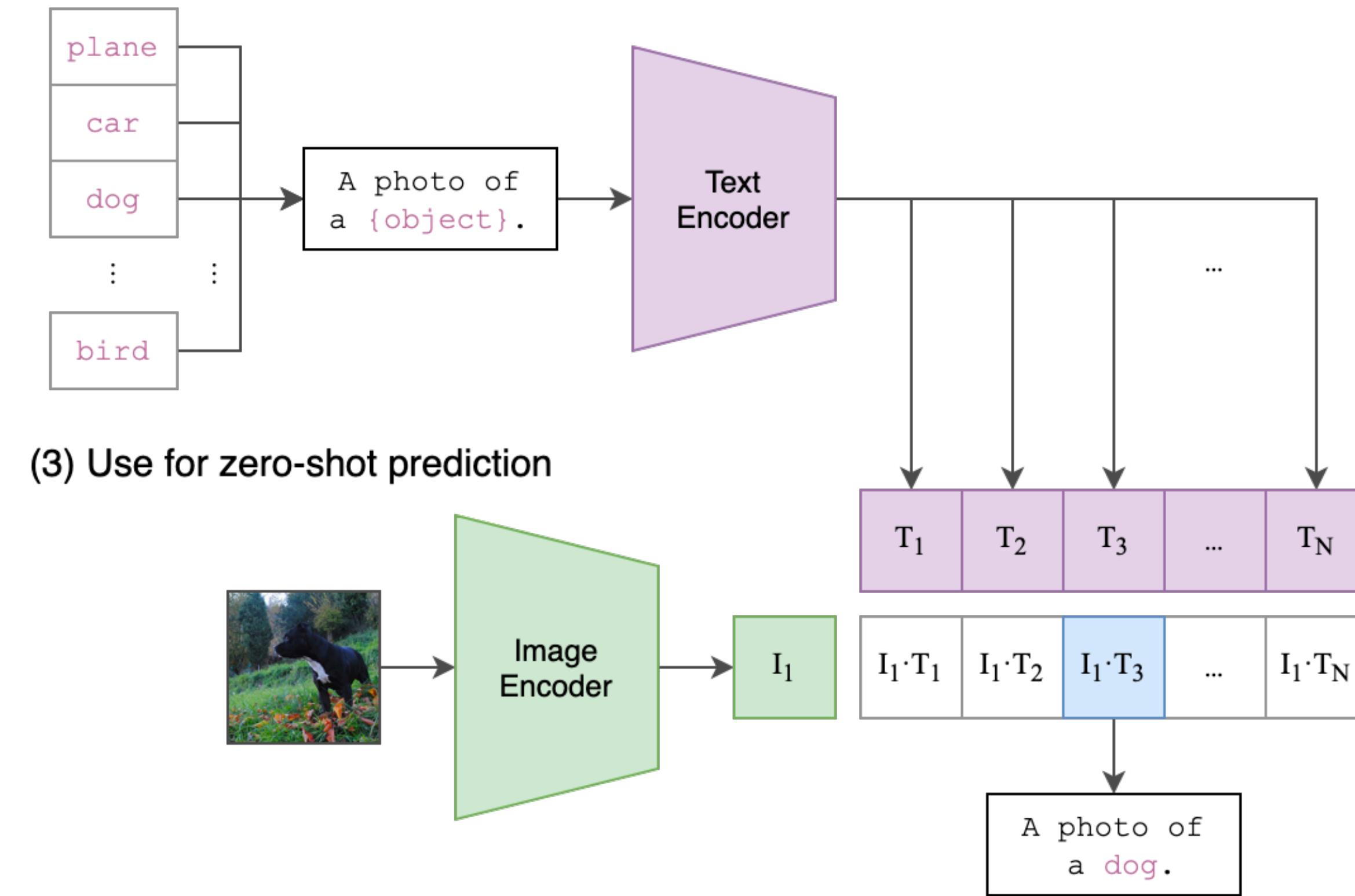
INVASIVE DUCTAL CARCINOMA,
DUCTAL CARCINOMA IN SITU,
MICROPAPILLARY AND SOLID
TYPES WITH COMEDO NECROSIS.
DUCTAL CARCINOMA IN SITU IS
NEAR INFERIOR MARGIN.

CLIP

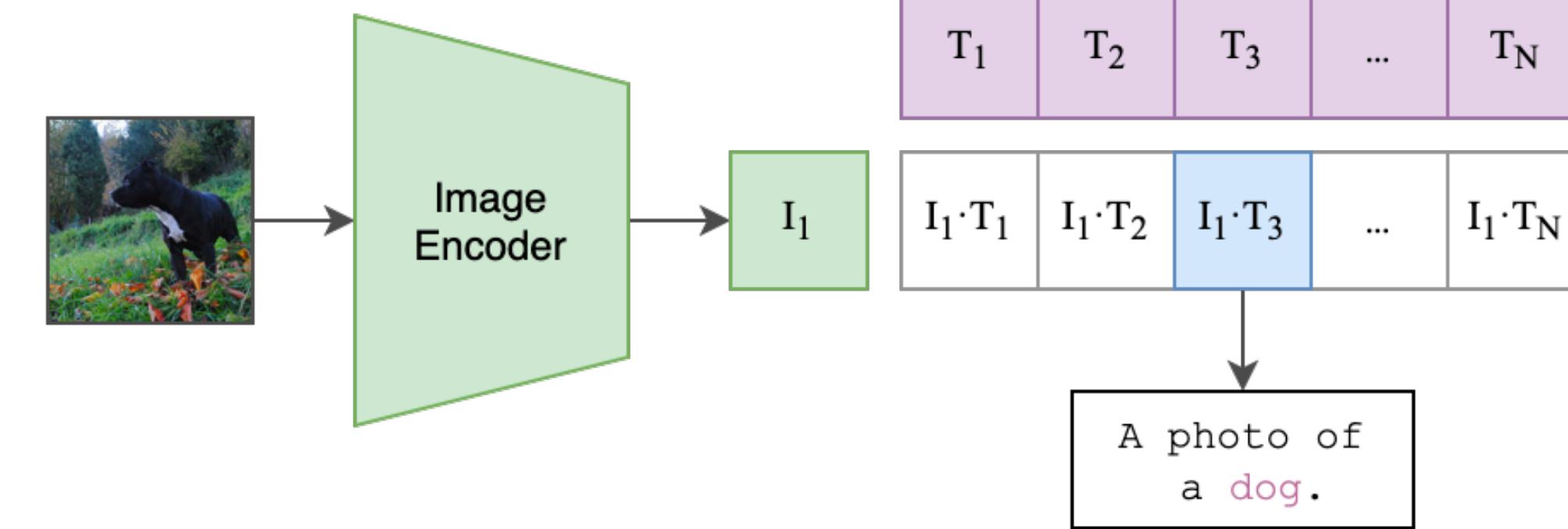
(1) Contrastive pre-training



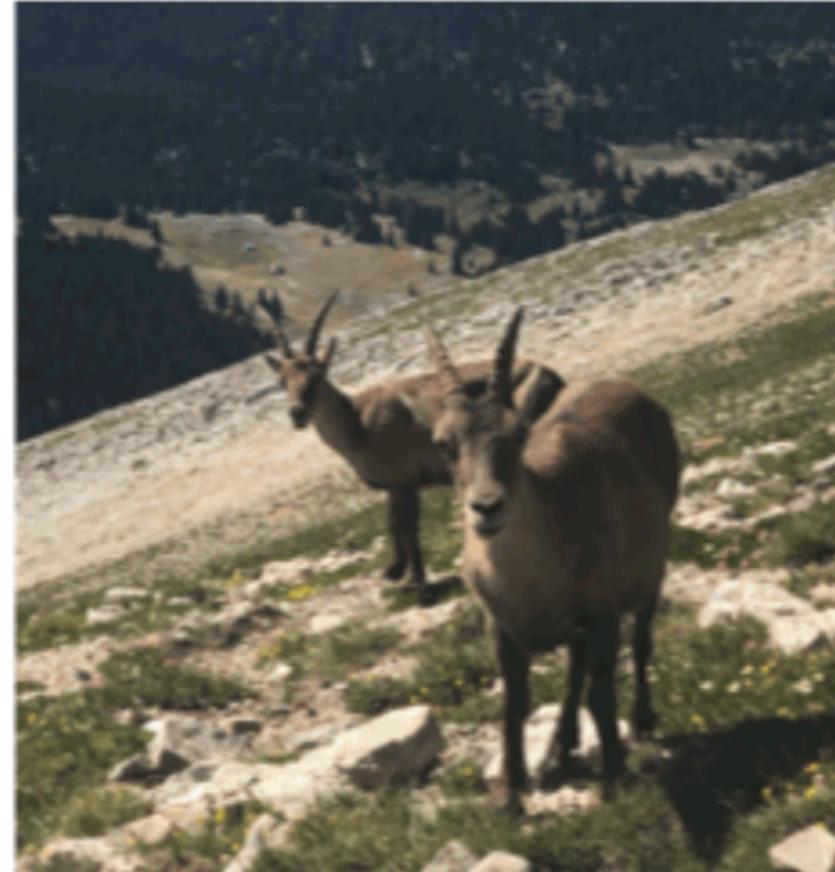
(2) Create dataset classifier from label text



(3) Use for zero-shot prediction



DINO

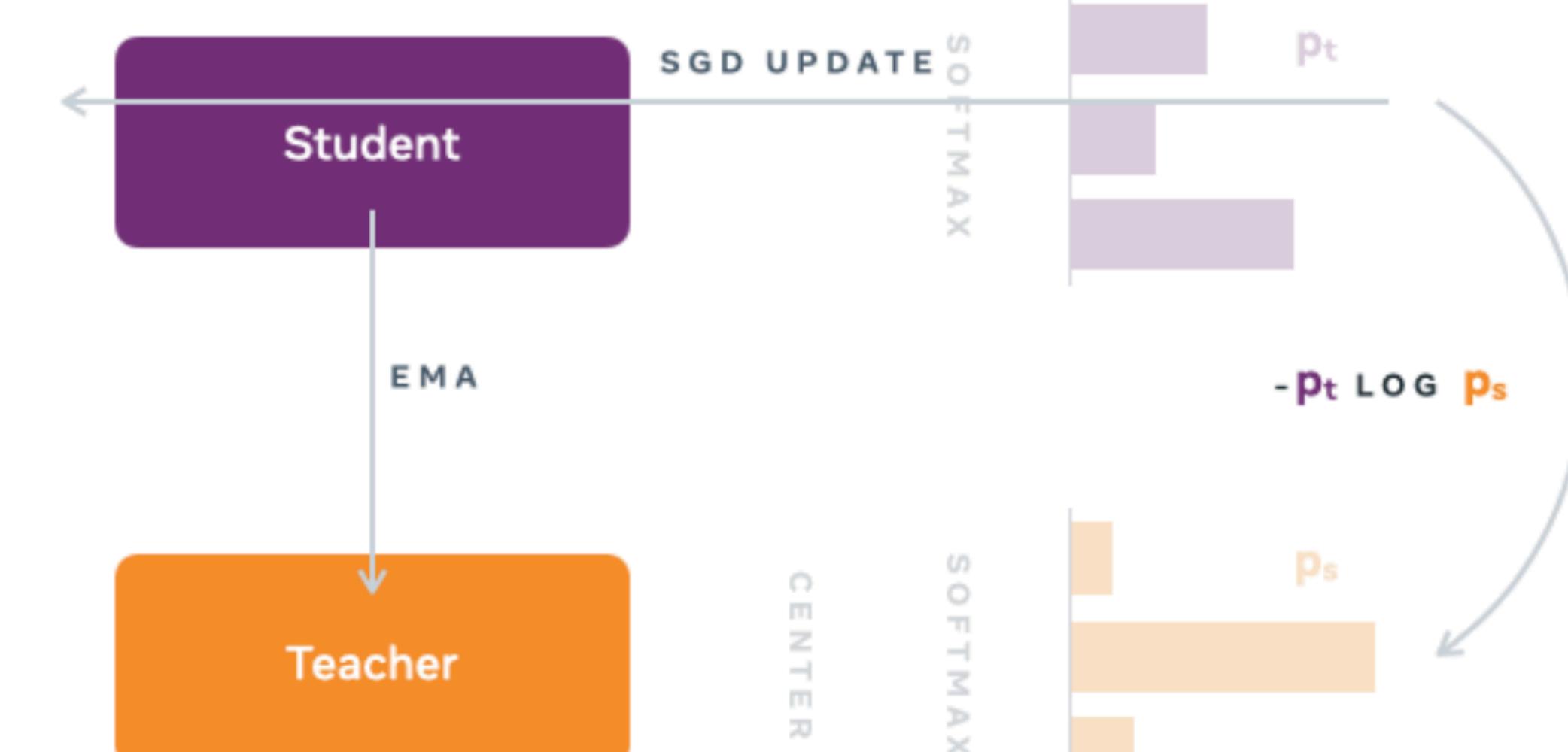


Student

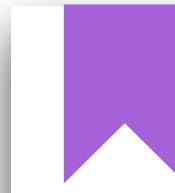
Teacher



DINO



Pathology BERT



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

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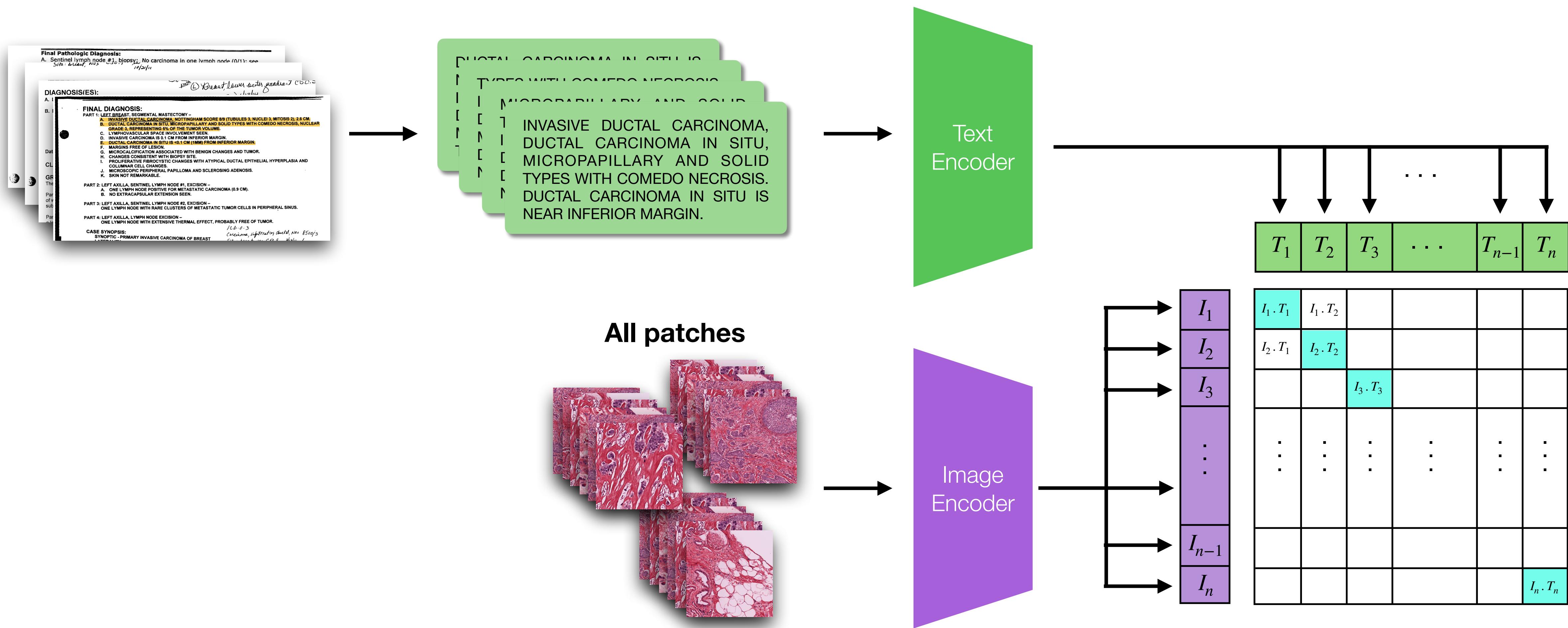
Change Tokenizer

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 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.

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

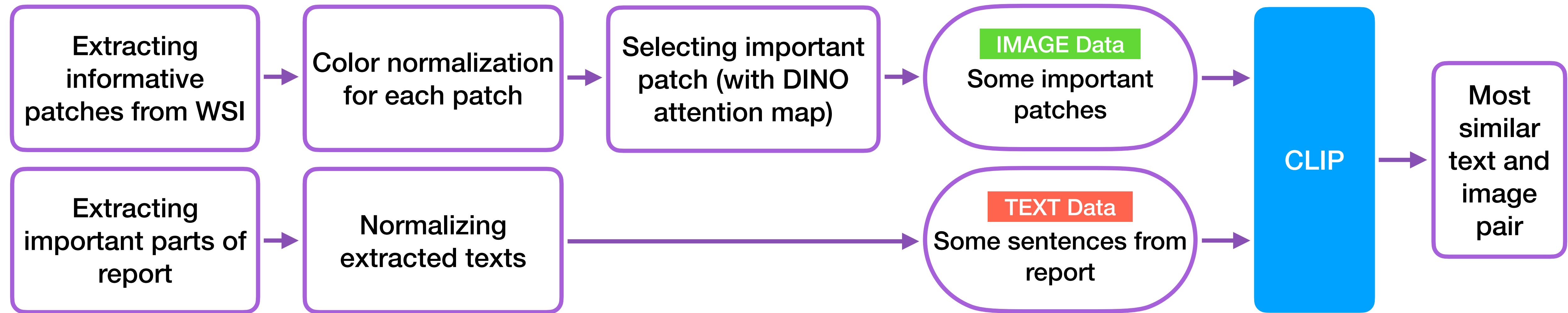
Baseline

Baseline model

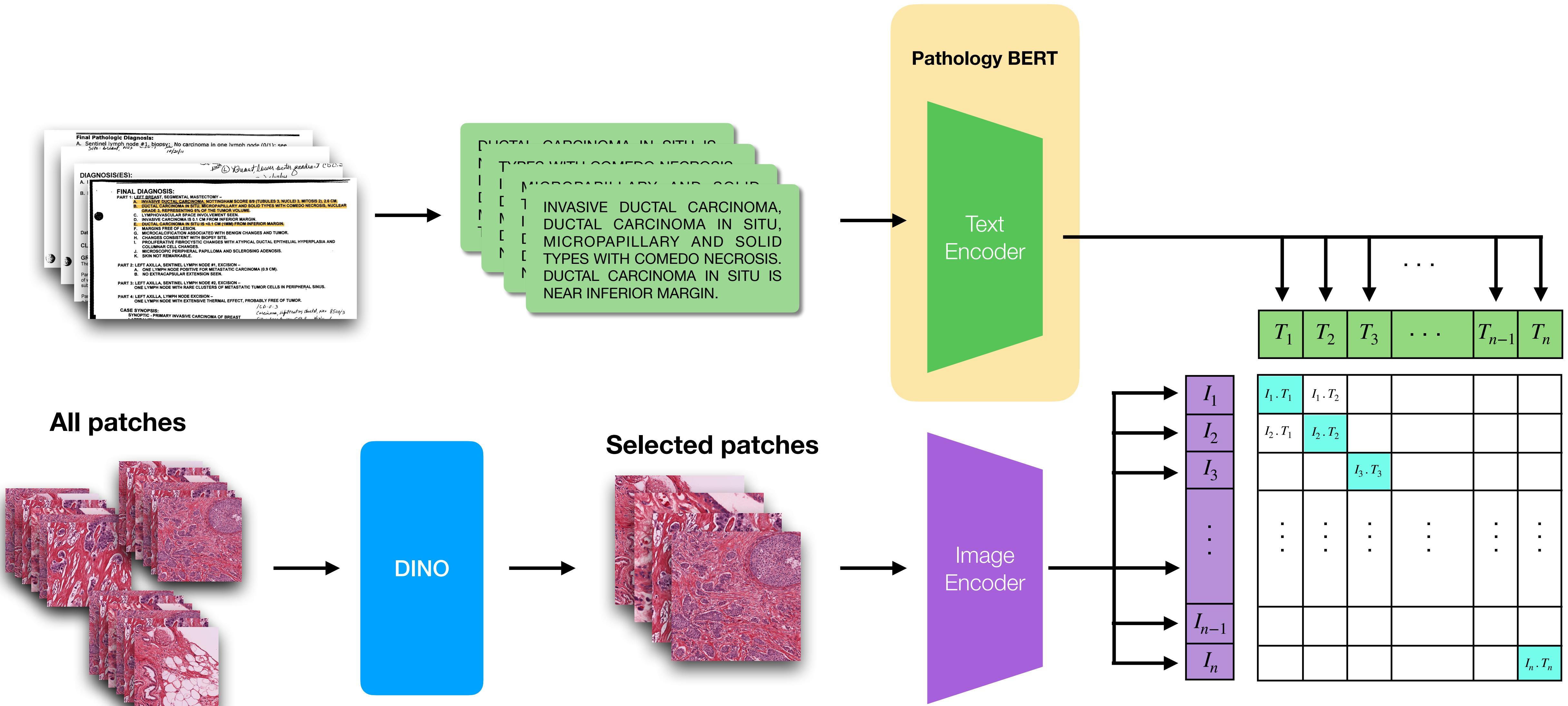


Proposed Model

Pipeline



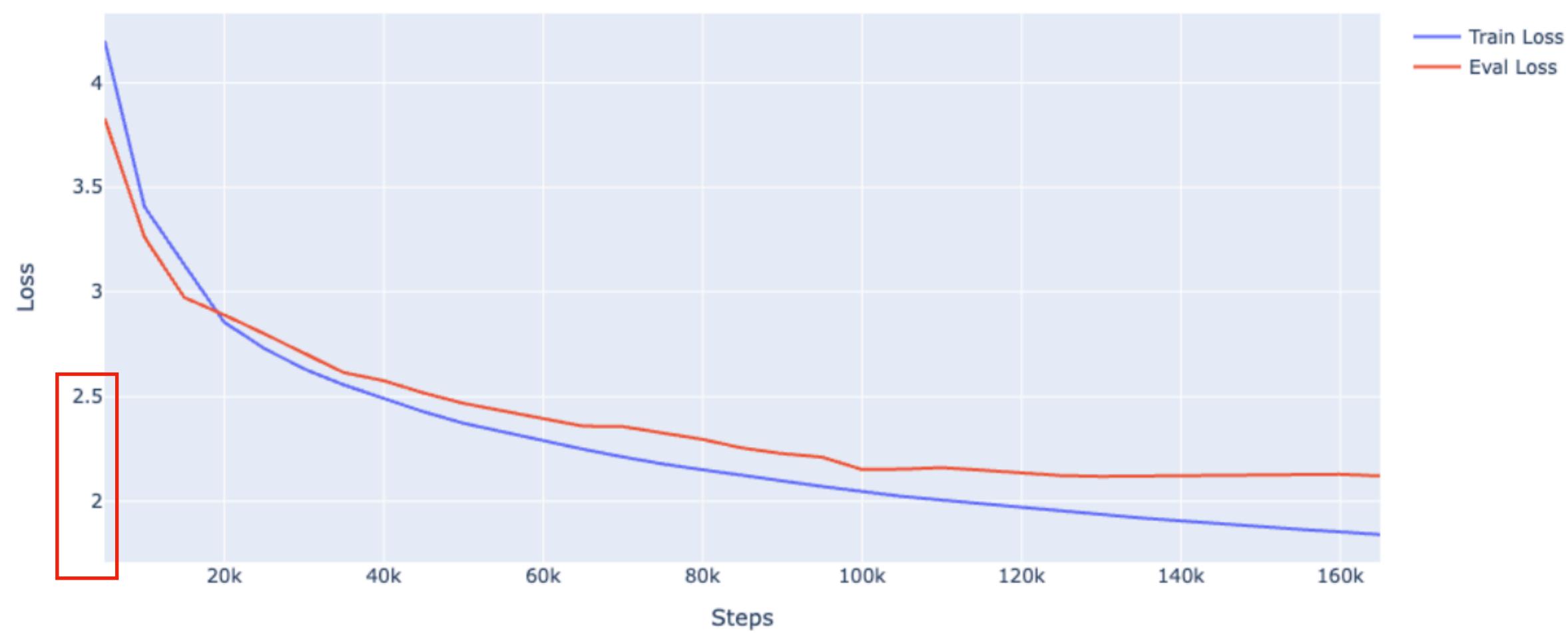
CLIPPath



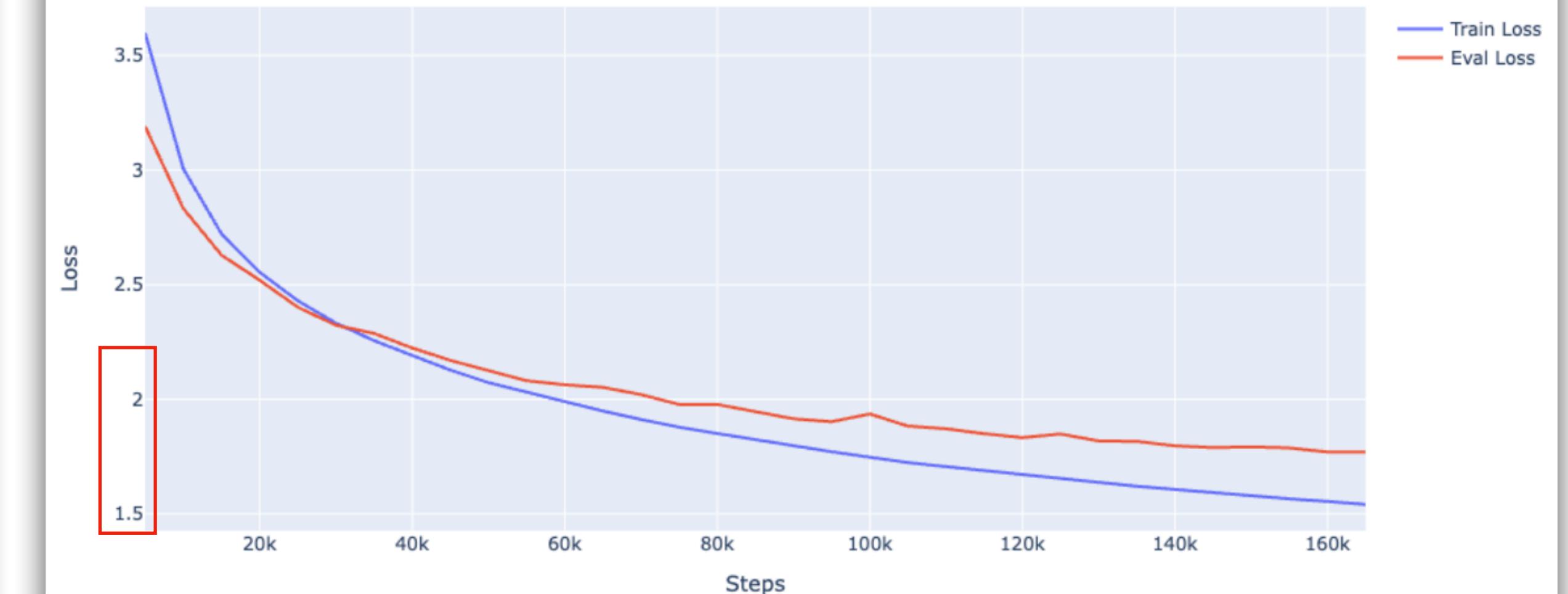
Results

Results

Train Loss vs Eval Loss baseline Model



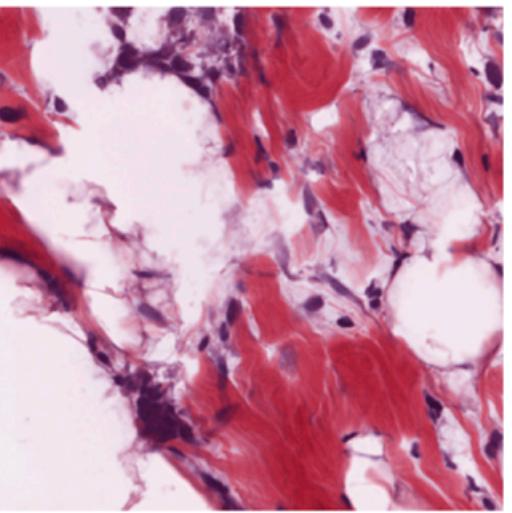
Train Loss vs Eval Loss proposed Model



Results

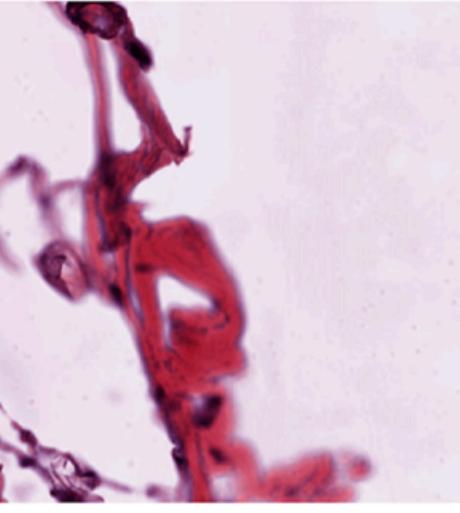
	Baseline model	CLIPPath model
Accuracy	0.525	0.698
Top-5 Accuracy	0.57	0.72

Results



Baseline	38%
	invasive 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%
	invasive ductal carcinoma, ducal carcinoma in situ
	21%
	invasive lobular carcinoma in greatest linear dimension.

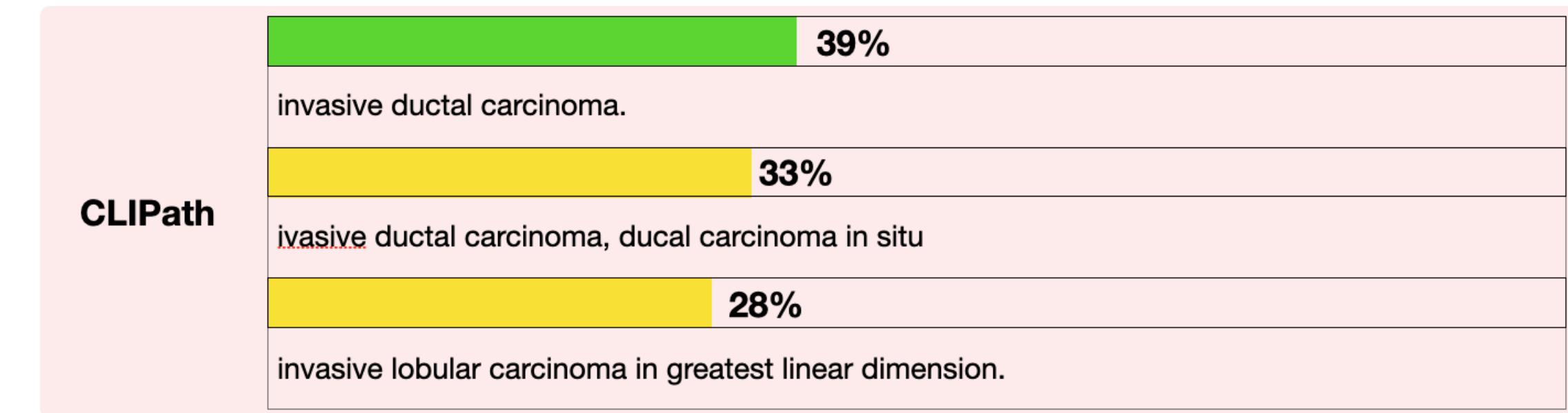
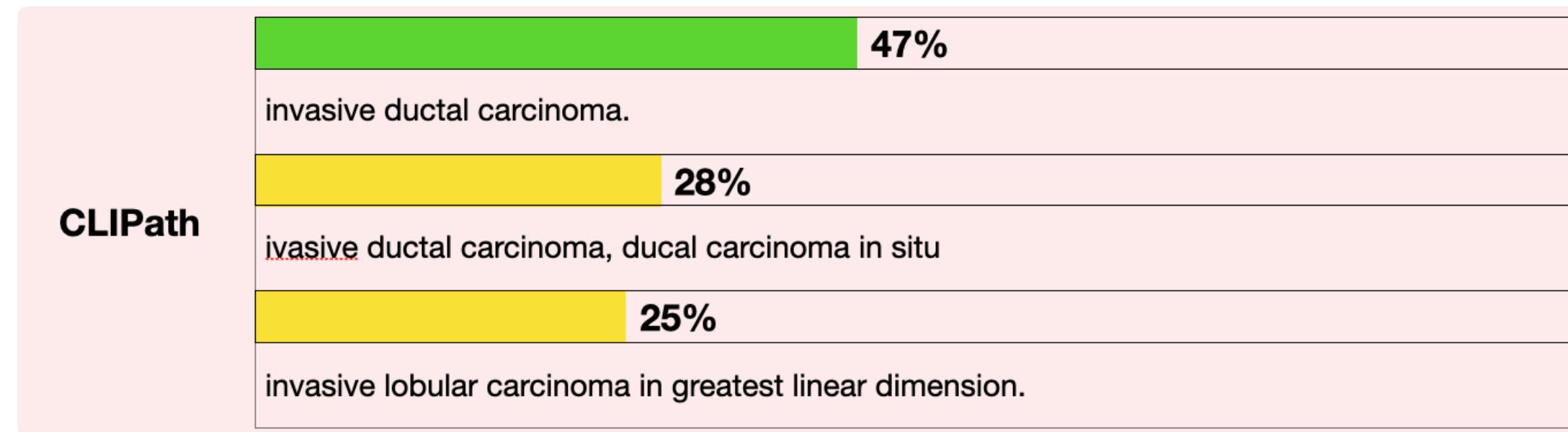
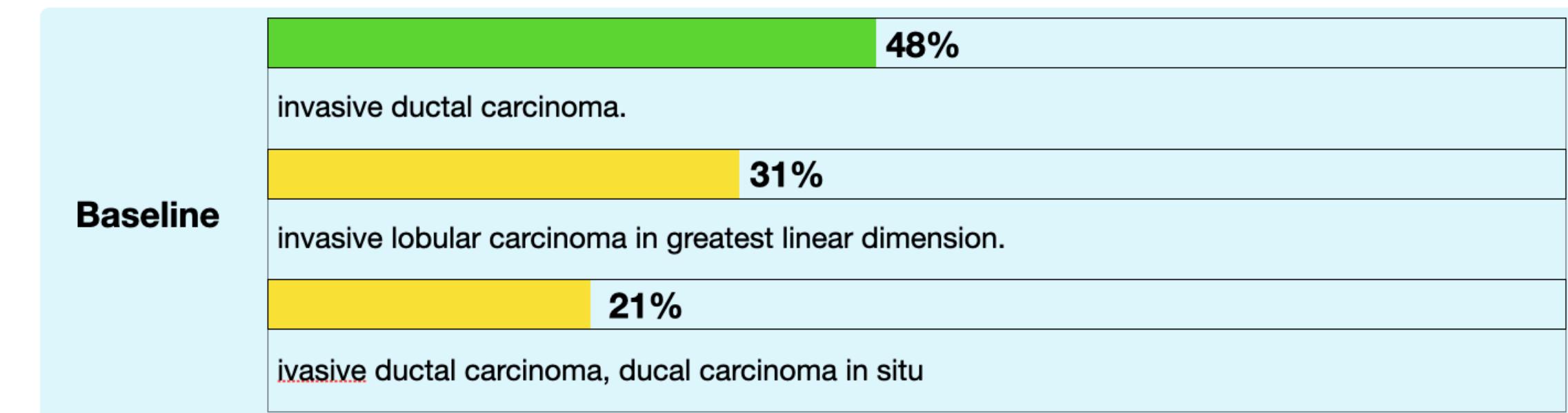
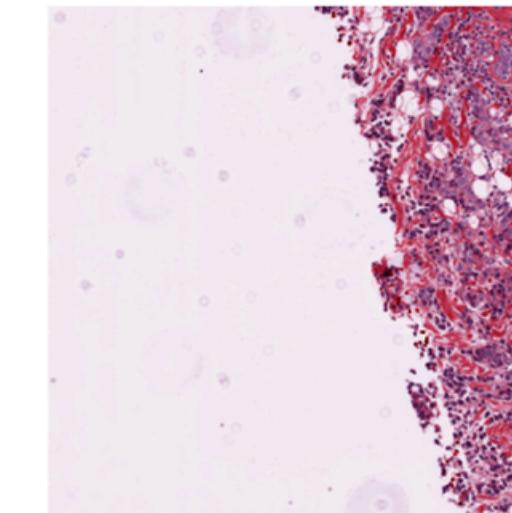
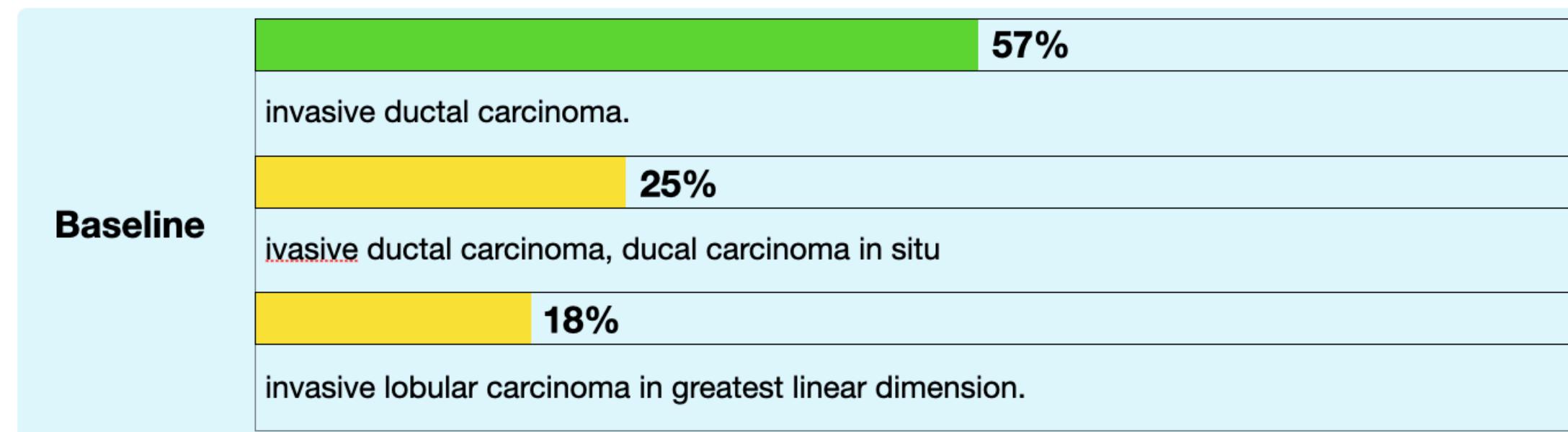
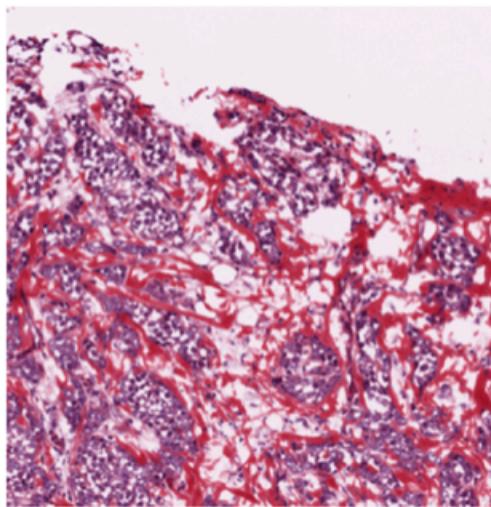


Baseline	46%
	infiltrating ducal carcinoma.
	27%
	invasive ductal carcinoma, ducal carcinoma in situ
	27%
	invasive lobular carcinoma in greatest linear dimension.

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

1024×1024

Results



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 :)