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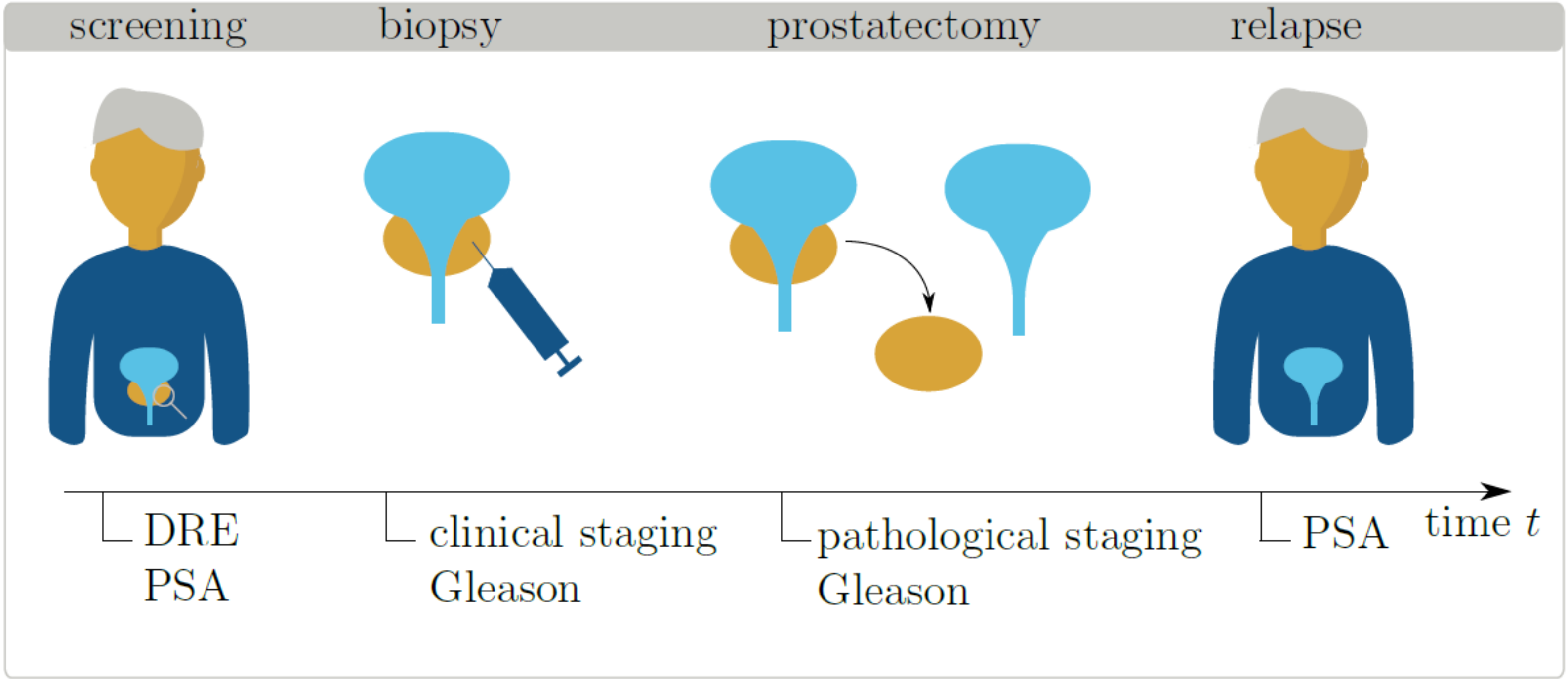
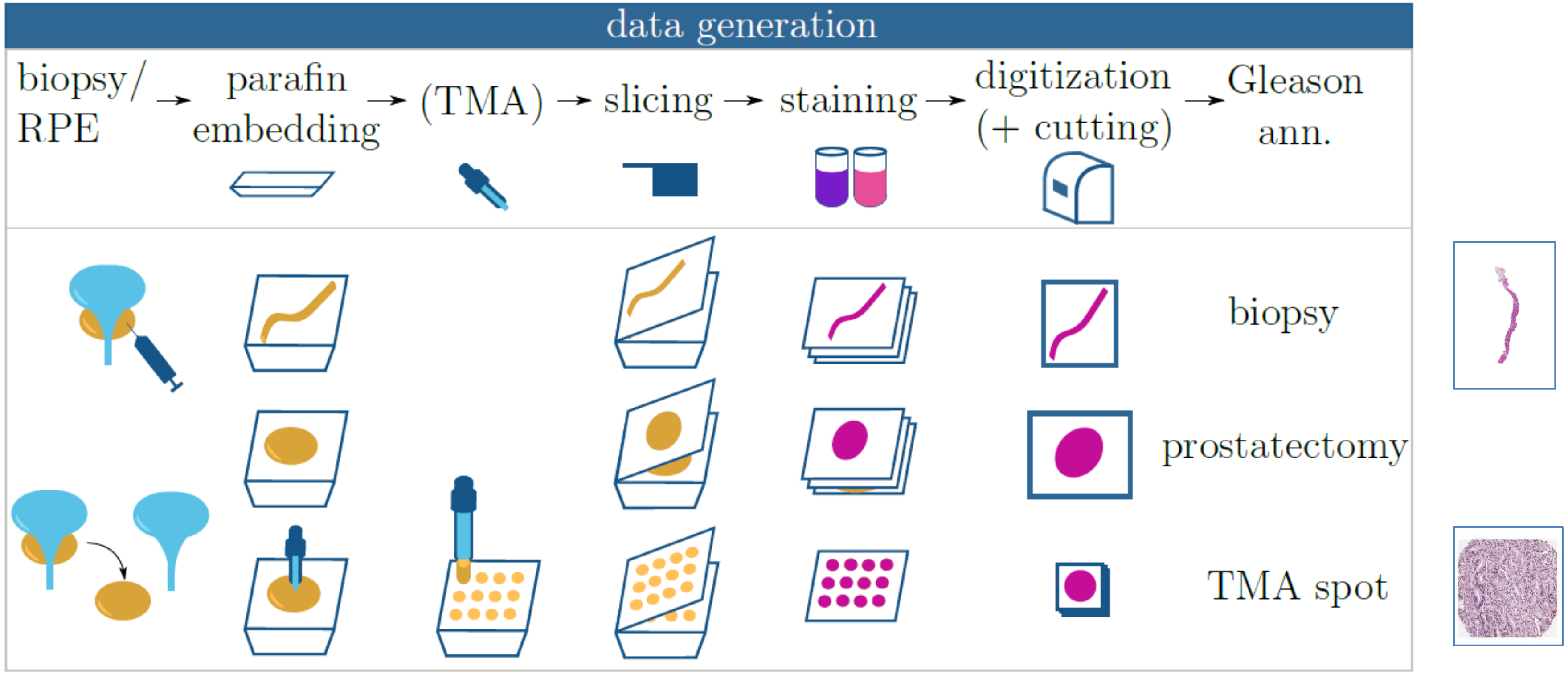
Relapse Prediction of Prostate Cancer with Histopathology Images using Vision Transformers

IMSB

Introduction: Prostate cancer



Data acquisition



Dietrich(2022)

Introduction: Relapse prediction

- Gleason grade is subjective
- High interrater variability between pathologists – ambiguity in diagnosis and therapy
- Biochemical relapse prediction has objective endpoint
- Generate binary label
  - If event occurs before 60 months : positive
  - If event does not occur : negative

RESEARCH QUESTIONS

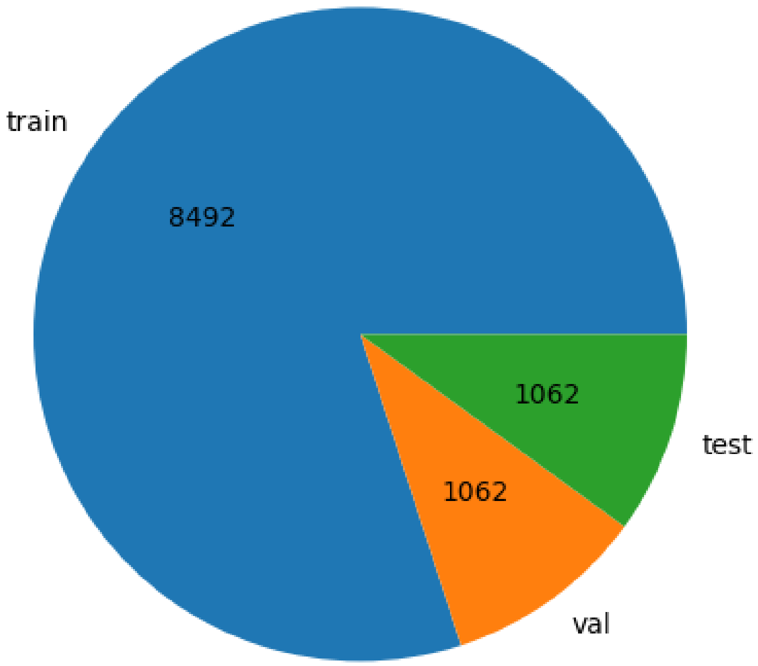
Research questions

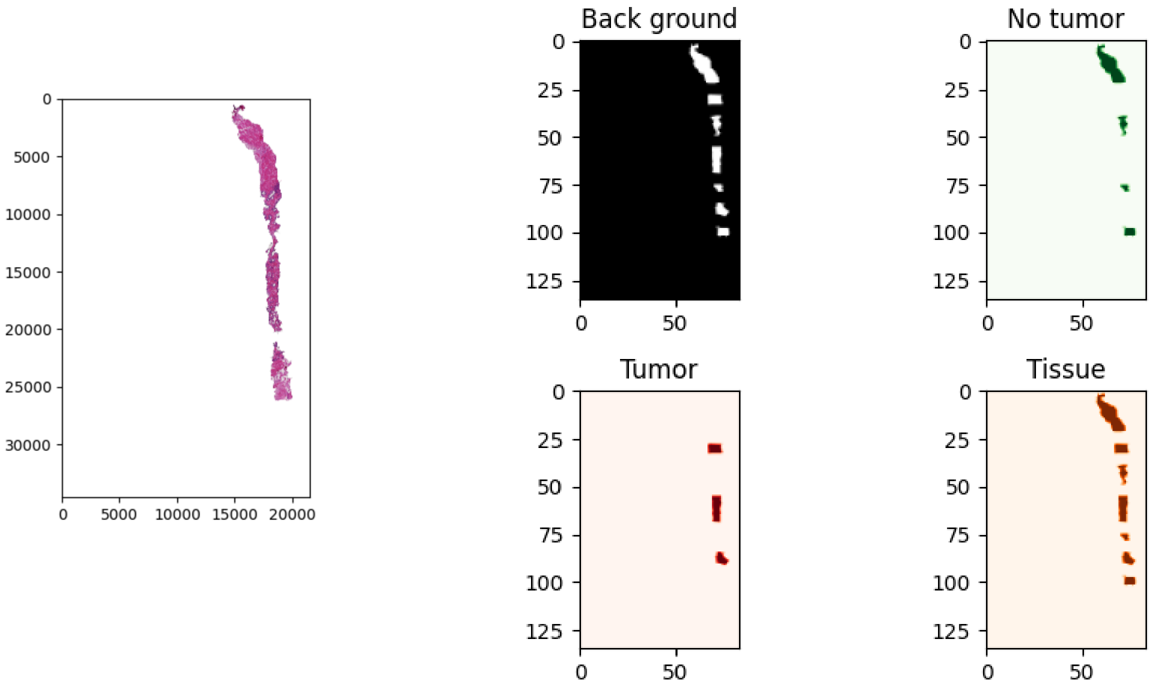
- **R1:** How well can state-of-the-art **vision transformers** (ViT) predict relapse of prostate cancer on our in-house data?
- **R2:** Does **pre-training** ViT on **domain-specific** images improve the performance of the model?
- **R3:** How good are **hierarchical vision transformers** on our in-house prostate cancer data?

DATASETS

Datasets

- PANDA challenge for cancer detection
  - Prostate cANcer graDe Assessment
  - Size: 5,000 to 40,000 pixels per dimension
  - 10,616 images

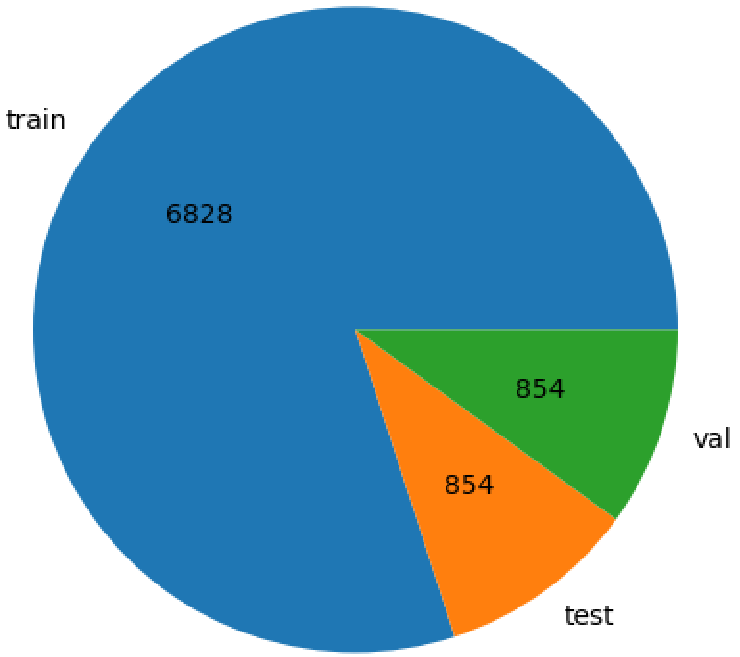


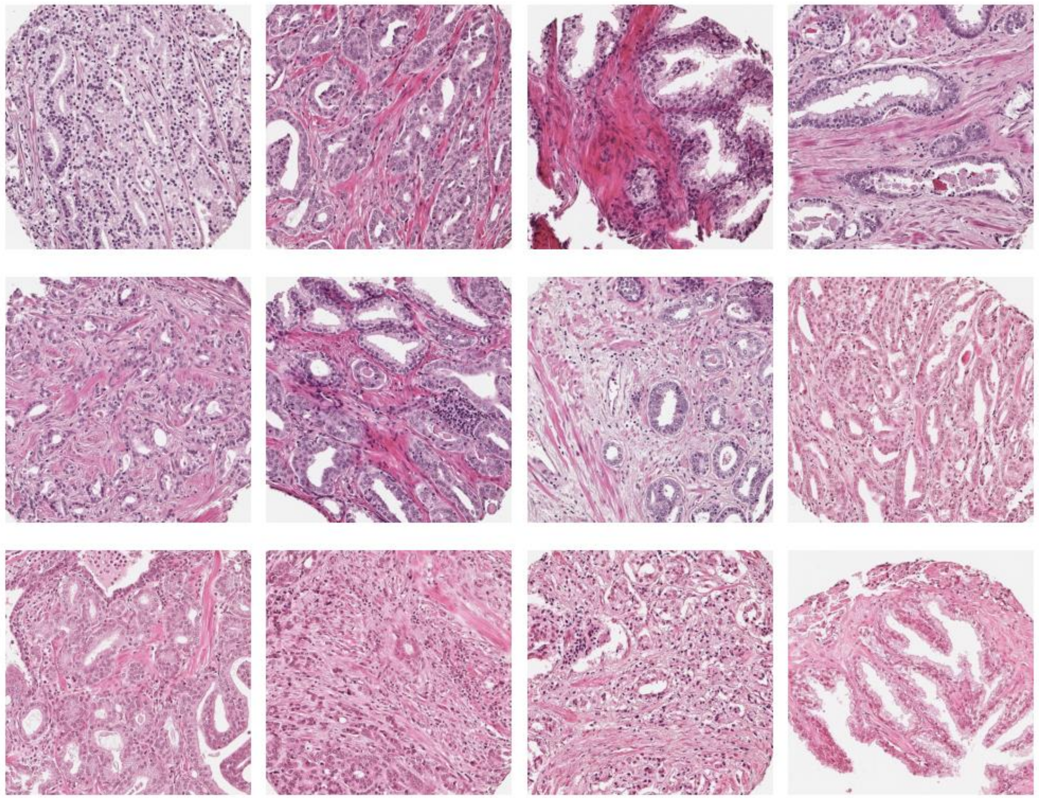


https://www.kaggle.com/competitions/prostate-cancer-grade-assessment/data

Datasets

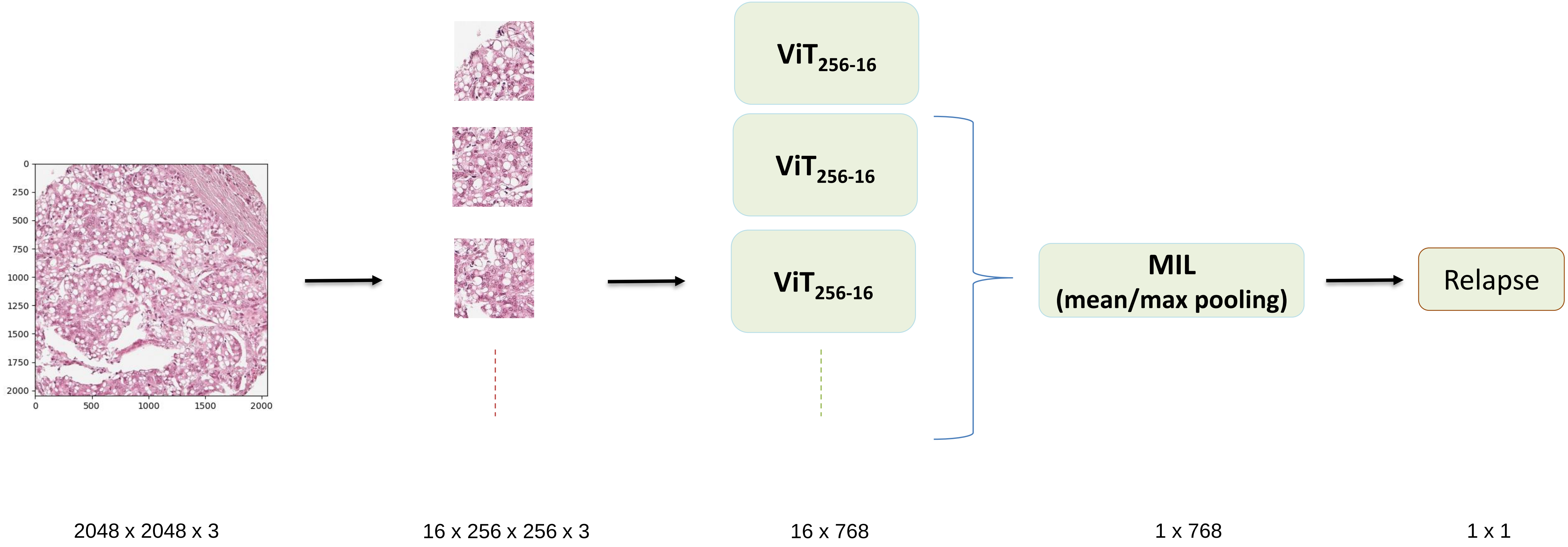
- UKE dataset for relapse prediction
  - TMA spots
  - Size: 2048 x 2048 pixels
  - 8536 images



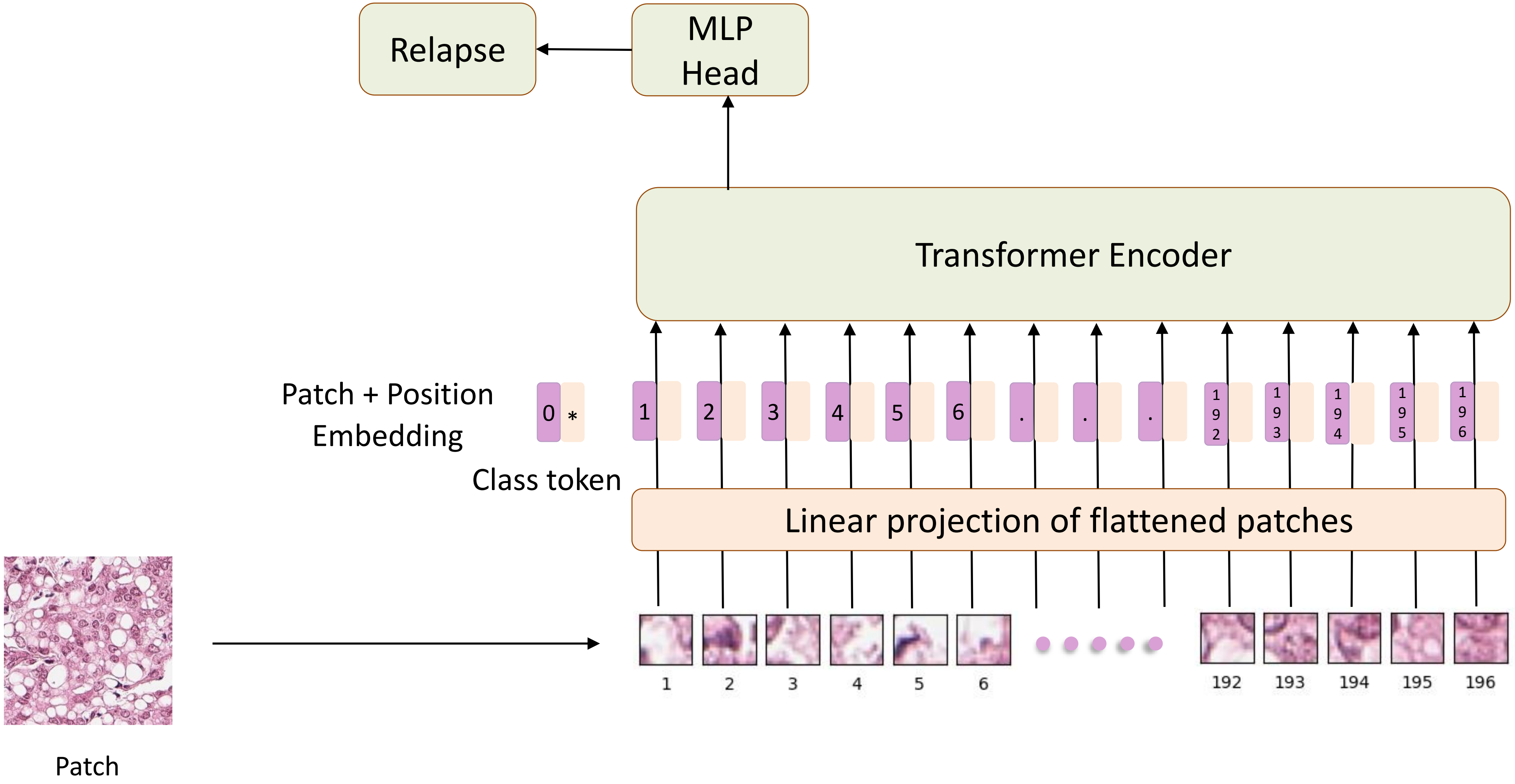


METHODS

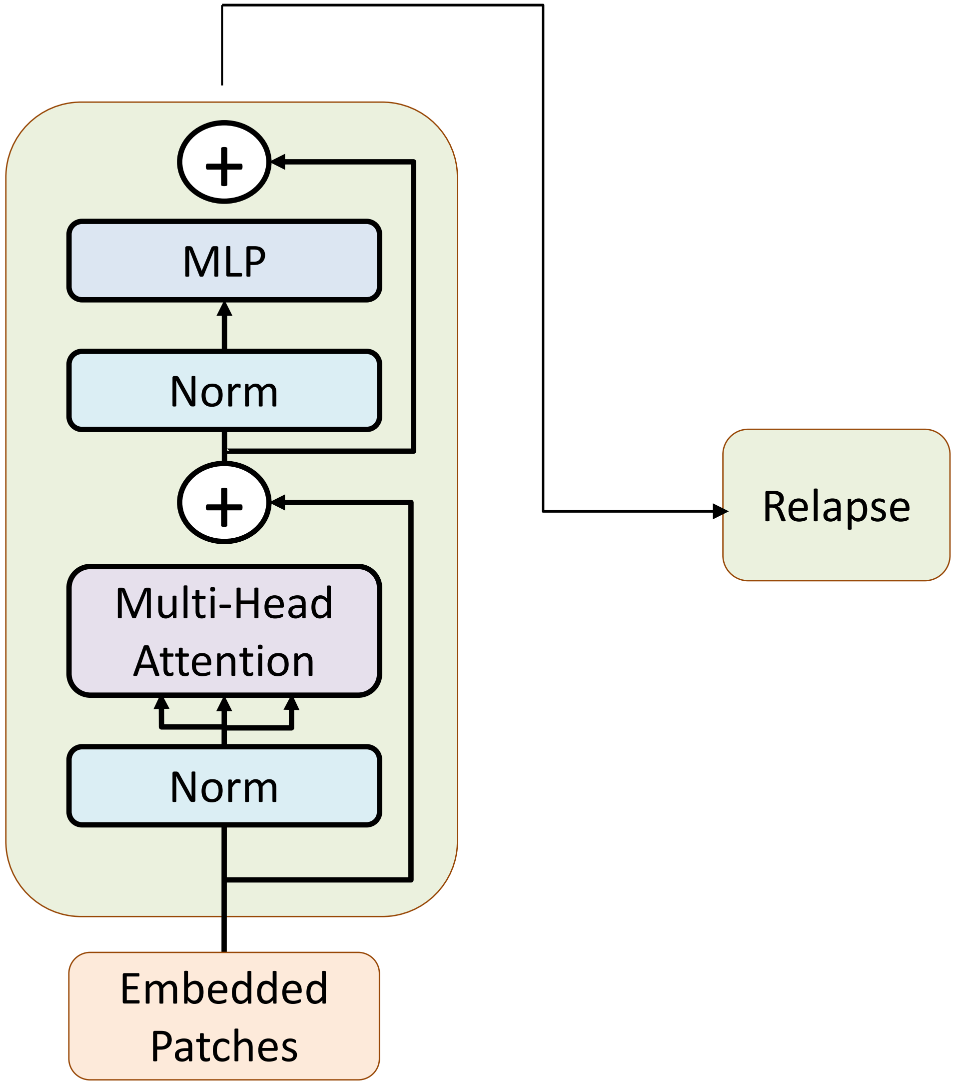
Vision transformers with multiple instance learning



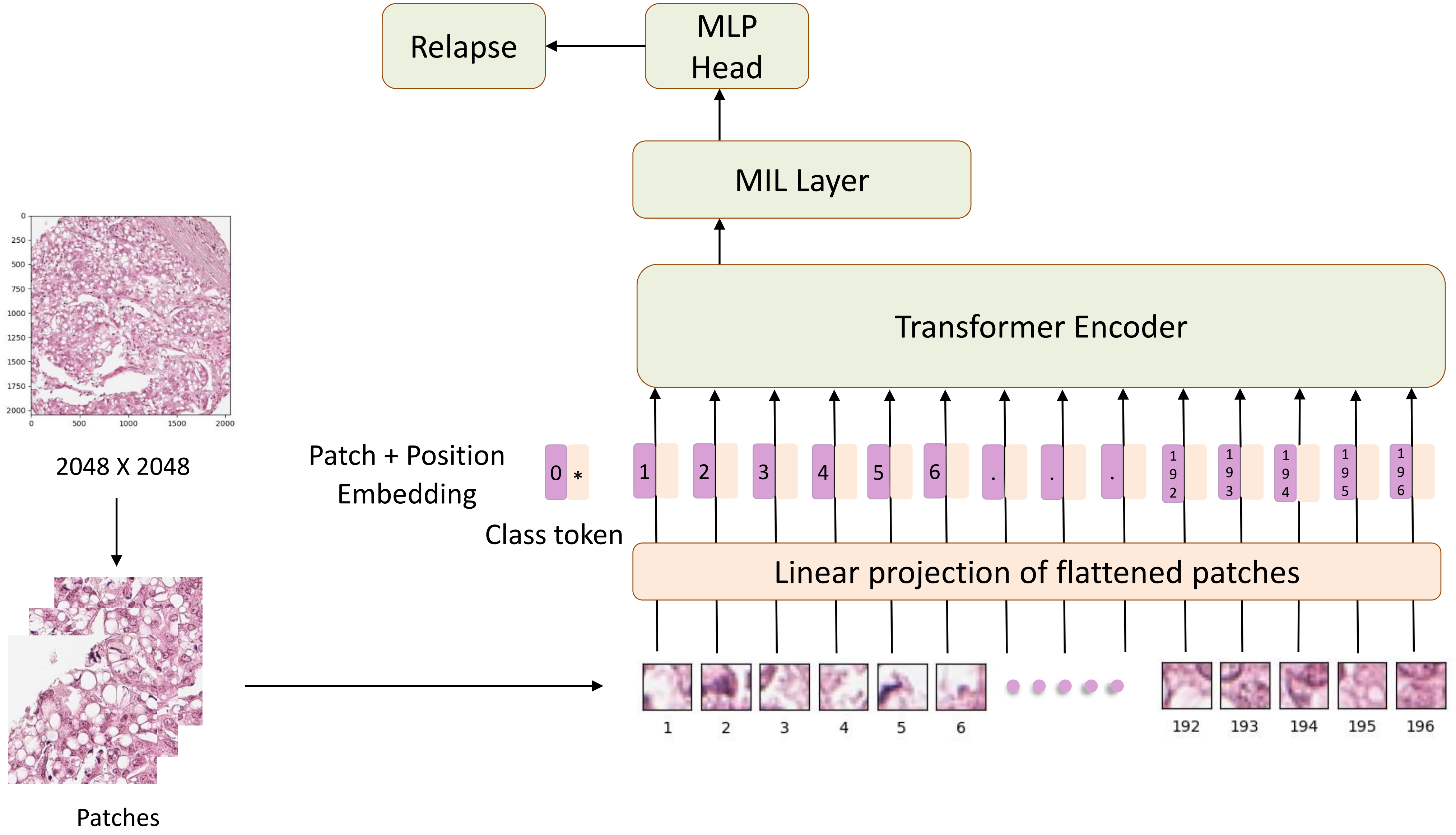
ViT on single patch



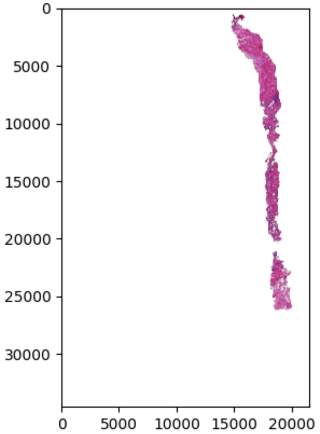
ViT encoder


MLP
Norm
Multi-Head
Attention
Norm
Embedded
Patches
Relapse

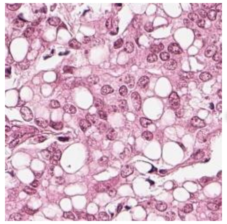
ViT for TMA spot



Pre-training of ViT on cancer detection



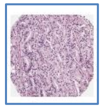
→ Patch selection →

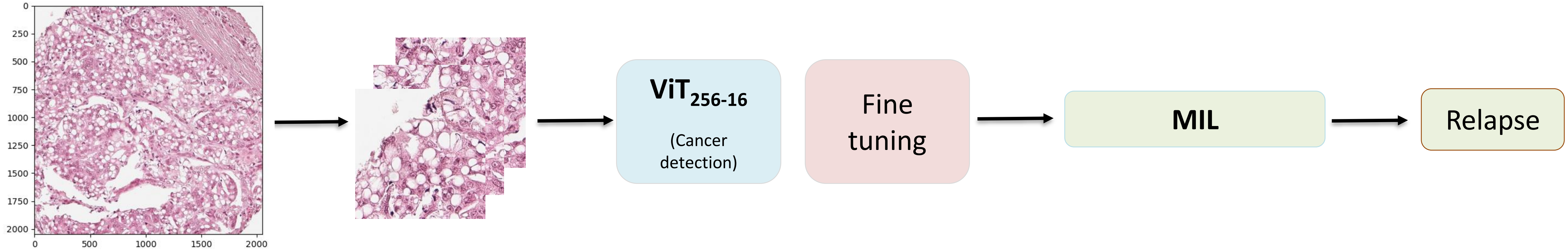


→ $\mathbf{ViT}_{256\text{-}16}$ → Cancer detection

PANDA image

Relapse prediction on PANDA pre-trained ViT





2048 x 2048 x 3

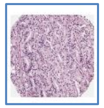
16 x 256 x 256 x 3

16 x 768

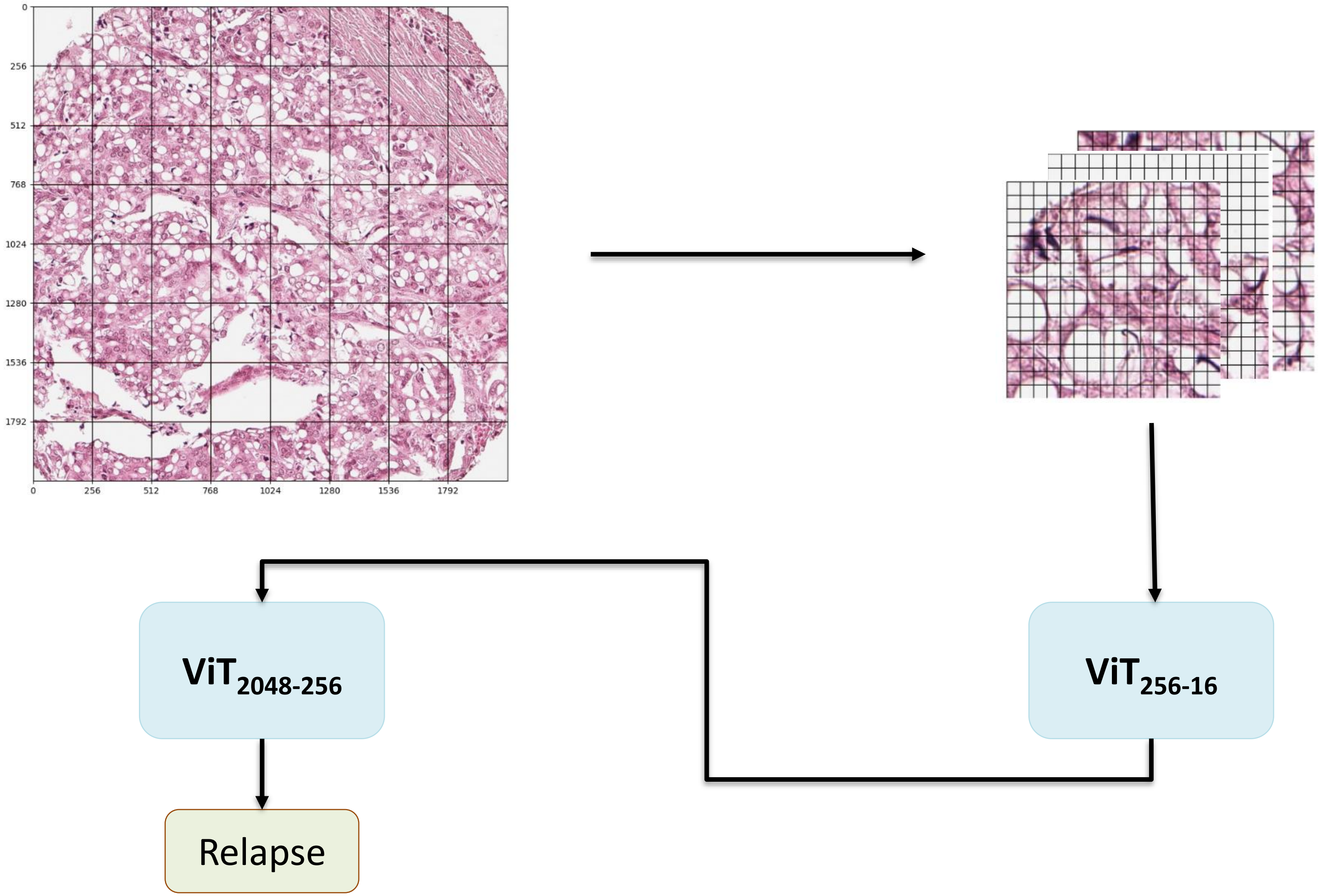
1 x 768

1 x 1

Hierarchical ViT

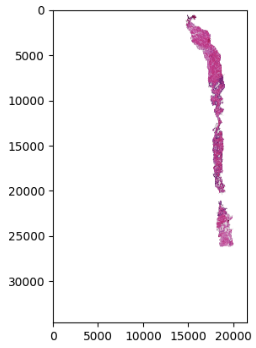


- As UKE dataset is of size 2048 x 2048, the intended approach has two levels of hierarchy



Hierarchical ViT

- Two pre-trainings : $\mathbf{ViT_{256\text{-}16}}$, $\mathbf{ViT_{1024\text{-}256}}$

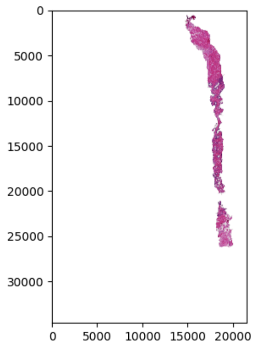


$\downarrow$

$\mathrm{ViT}_{256\text{-}16}$

$\downarrow$

Cancer



$\downarrow$

$\mathrm{ViT}_{1024\text{-}256}$

$\downarrow$

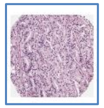
Cancer

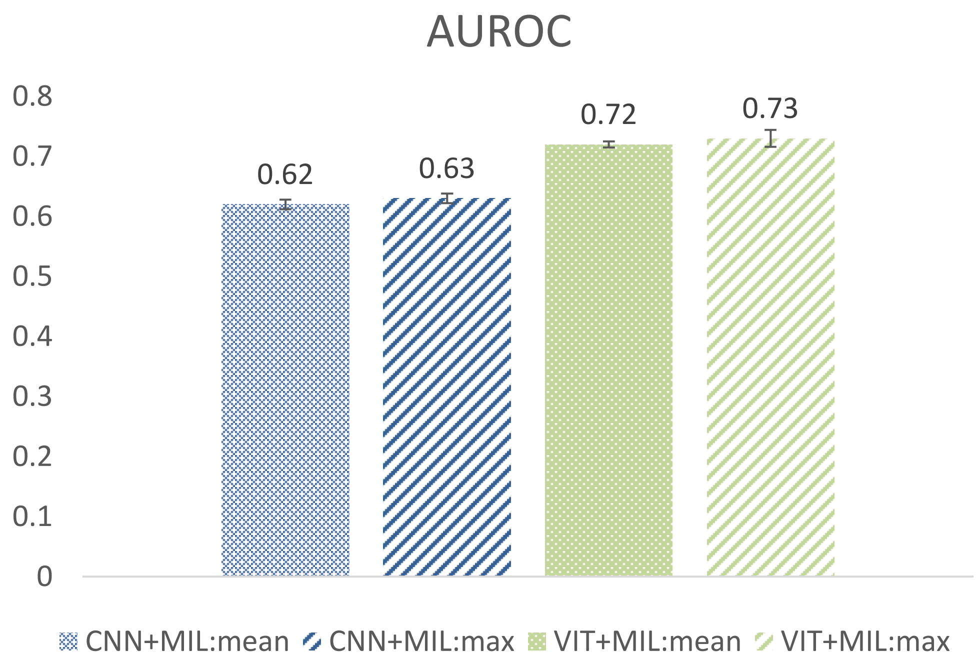
Methods

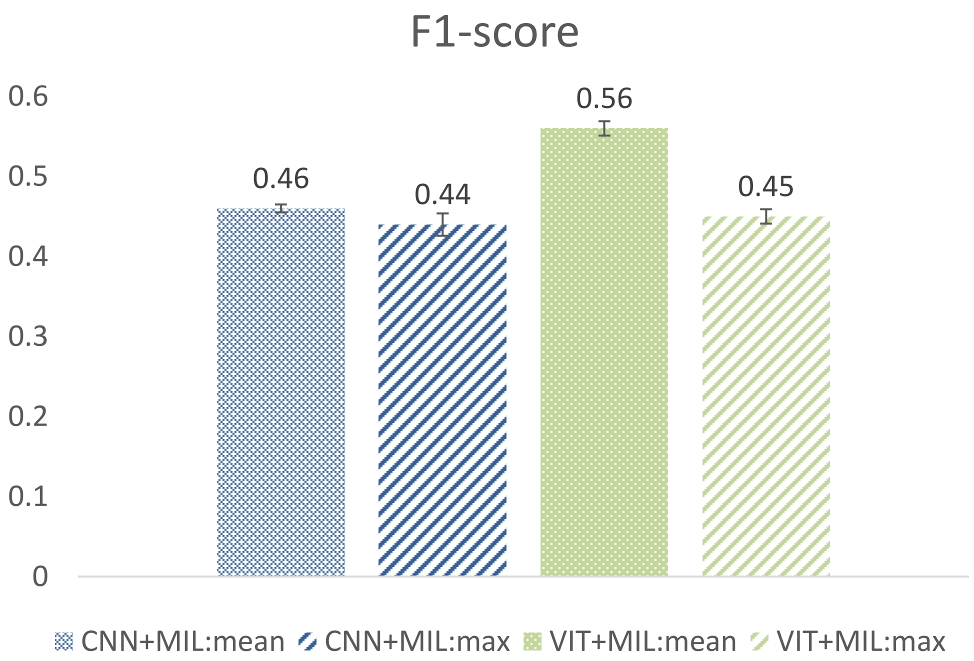
- Baseline model : CNN combined with MIL
- ViT+MIL: mean and max pooling for ImageNet and PANDA pre-training
- Hierarchical ViT

RESULTS

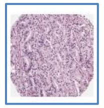
Results of CNN+MIL and ViT+MIL (ImageNet weights)

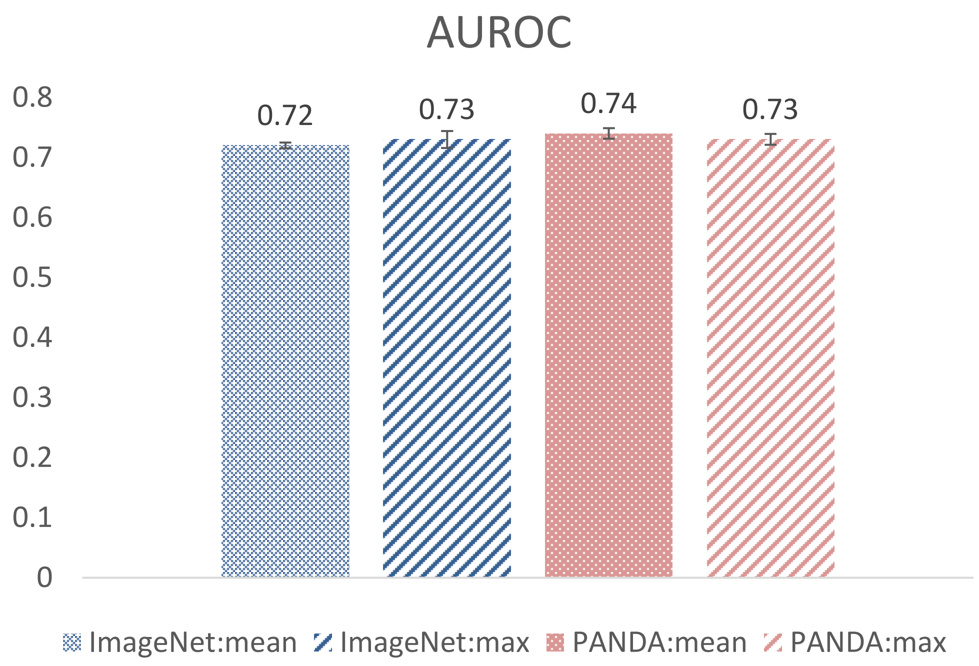


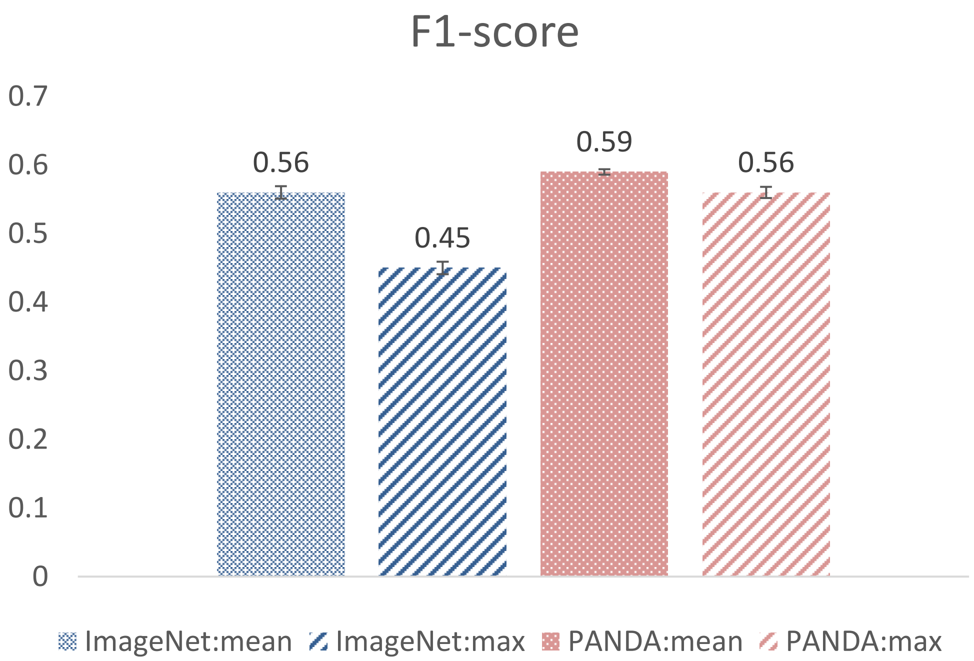




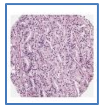
Results of ViT+MIL (ImageNet and PANDA weights)

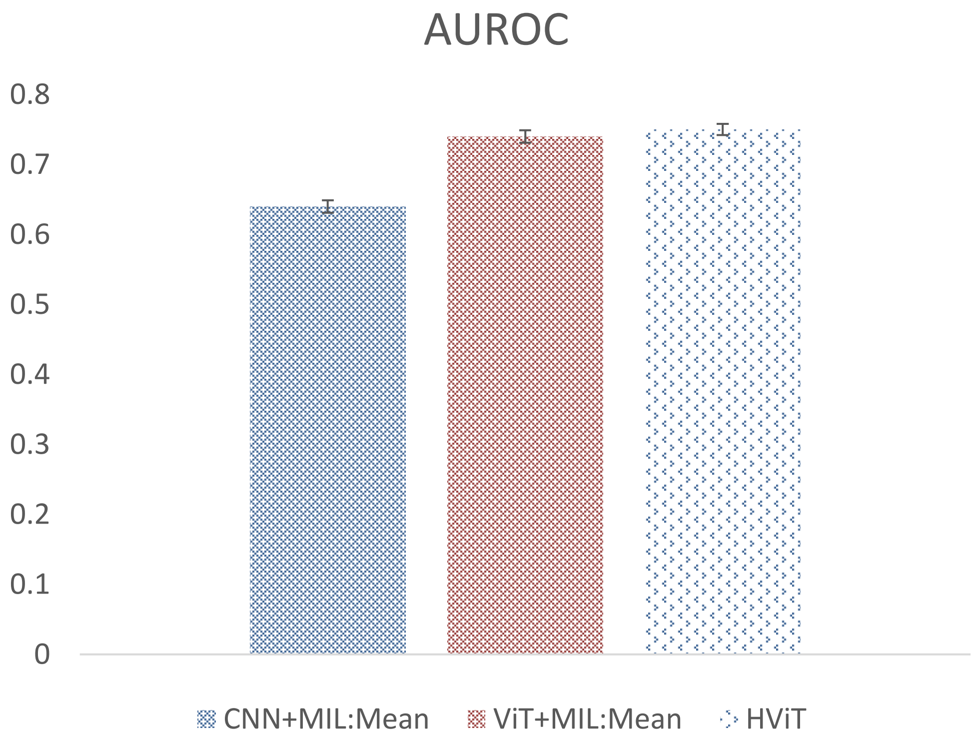


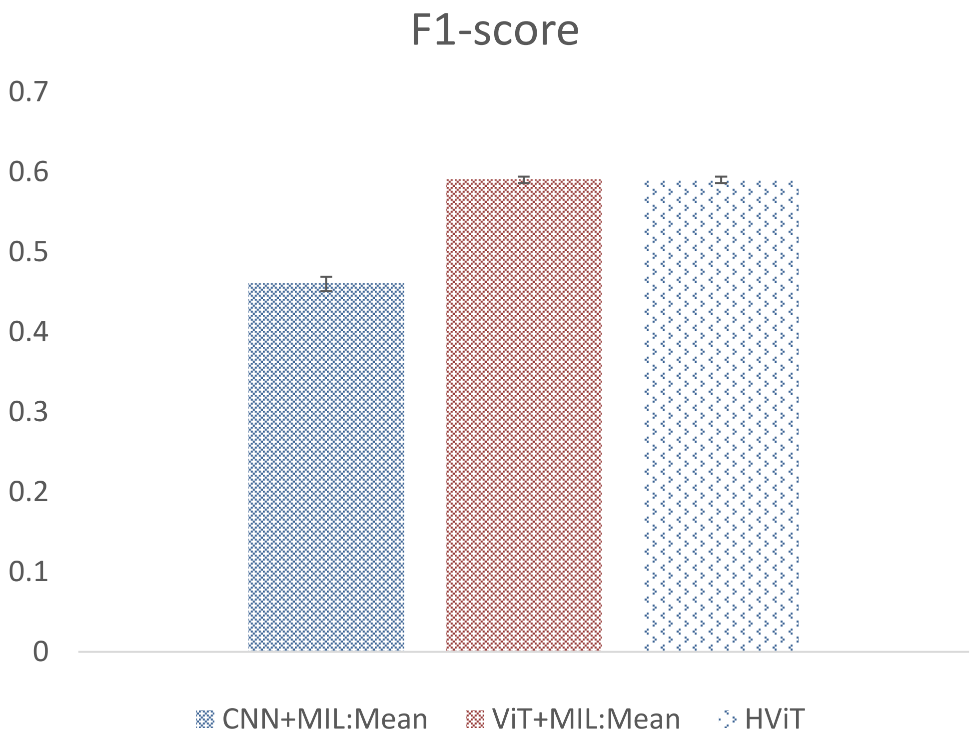




Results of HViT







Summary

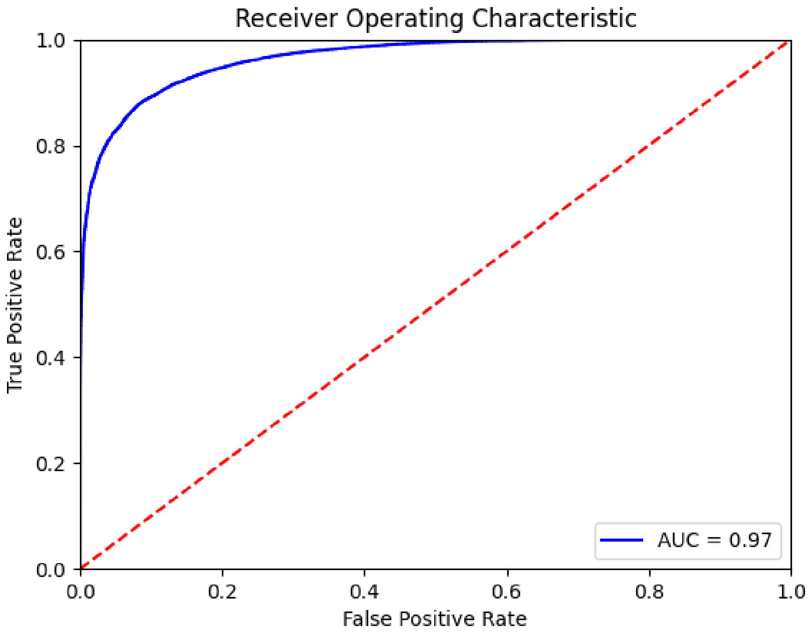
- **R1:** ViT outperformed CNN by 10 percent on AUROC and F1-score
- **R2:** Pre-training of ViT on domain-specific data did not have significant impact
- **R3:** Hierarchical ViT provided similar results compared to ViT+MIL

Further work

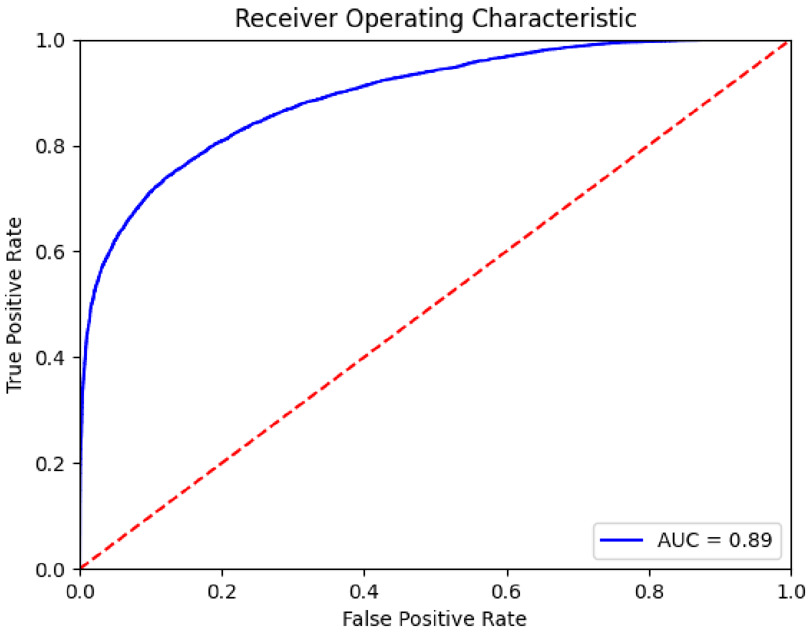
- Pre-train on more data
- Decrease model complexity (e.g. less encoder layers)
- Finetuning in multiple layers instead of only classification layer
- Other pre-training strategies (e.g. self supervised)

Thank you

Results of cancer detection

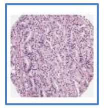


ViT



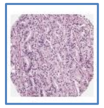
CNN

Results of CNN+MIL and ViT+MIL (ImageNet weights)



Model	Pooling strategy	AUROC	F1-score
CNN+MIL	mean	0.64±0.008	0.46±0.005
CNN+MIL	max	0.63±0.008	0.44±0.014
ViT+MIL	mean	0.72±0.005	**0.56±0.009**
ViT+MIL	max	**0.73±0.014**	0.45±0.009

Results of ViT+MIL (ImageNet and PANDA weights)



Model	Pretraining	Pooling strategy	AUROC	F1-score
ViT+MIL	ImageNet	mean	0.72±0.005	0.56±0.009
ViT+MIL	ImageNet	max	0.73±0.014	0.45±0.009
ViT+MIL	PANDA	mean	**0.74±0.009**	**0.59±0.004**
ViT+MIL	PANDA	max	0.73±0.009	0.56±0.008