DigiLut

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Team MaD Lab

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PhD Student

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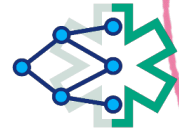Post-Doc

Lab

Machine Learning
Data Analytics

University

FAU

Project

Center for **AI**
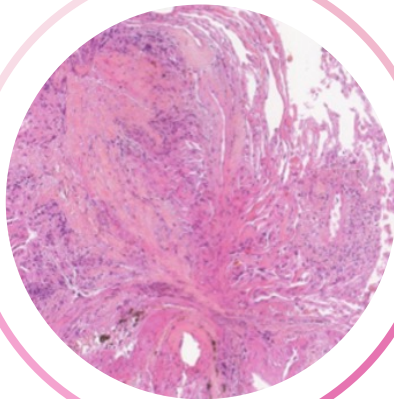in **M**edicine
Erlangen

The DigiLut Challenge

Research Question
Can AI accurately detect Type A lesions?

Dataset
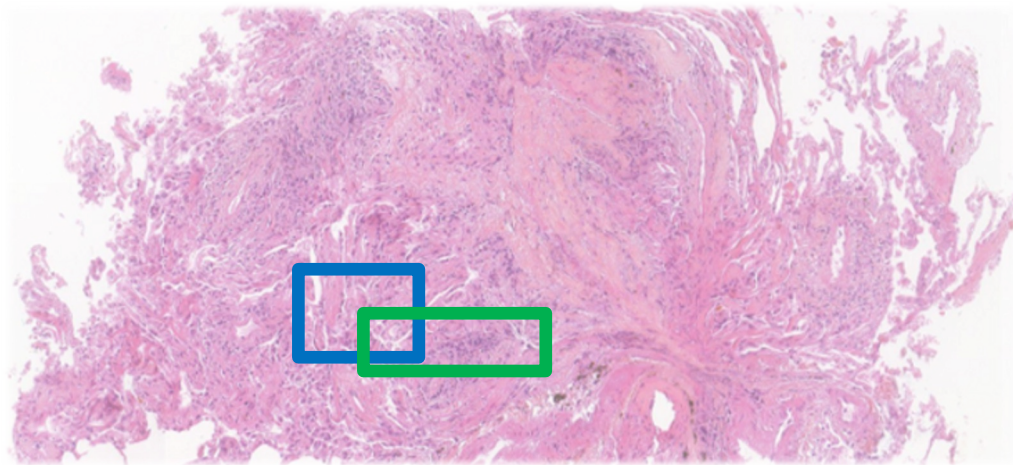2000 digitised lung biopsies 25% annotated

Task
Develop algorithm that detects Type A lesions

Translational Impact
AI based tool for detection of lung transplant rejection
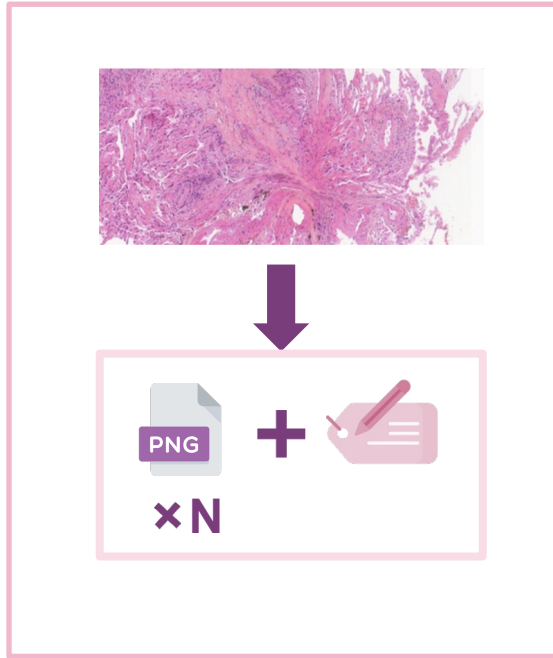
Goal of the Challenge

Goal

For a given Whole Slide Image, find **bounding boxes** of possible type A lesions.

A **bounding box** is **valid** if:
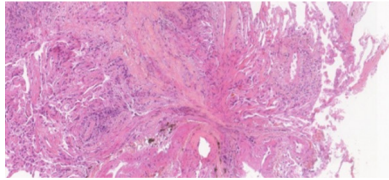Generalized Intersection over Union (**gIoU**) of prediction and ground truth **> 0.5**

Pipeline

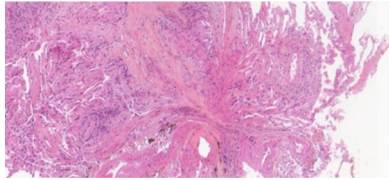**Dataset Creation**

Pipeline

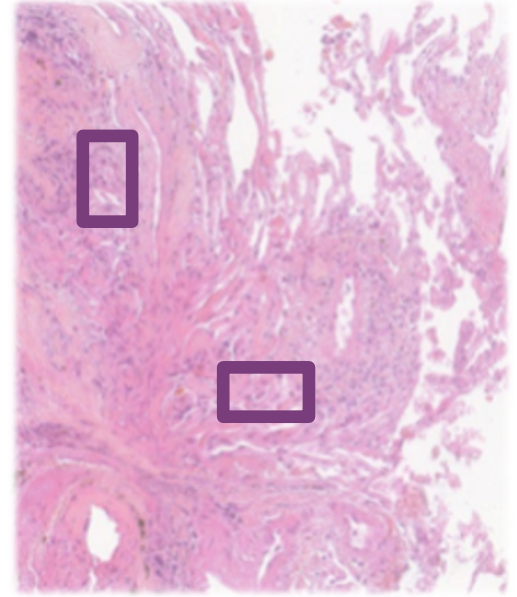## Dataset Creation

Model Training

Pipeline

Dataset Creation

Model Training

Prediction

Creating Patch Datasets
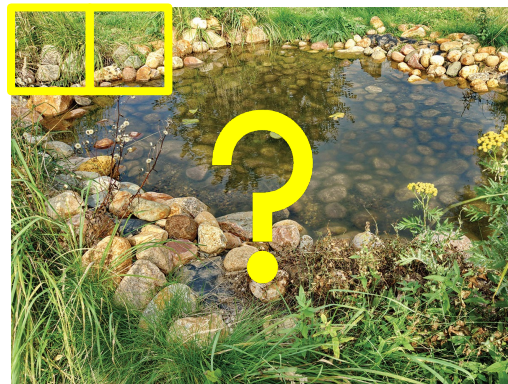
Region-of-Interest Detection

Object Detection

- Recent advances (Yolo models [1])

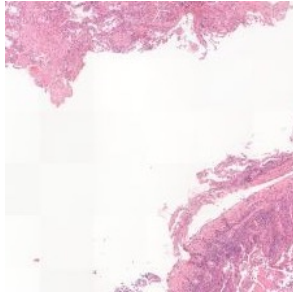- Challenging to apply to very large images

Patch Classification
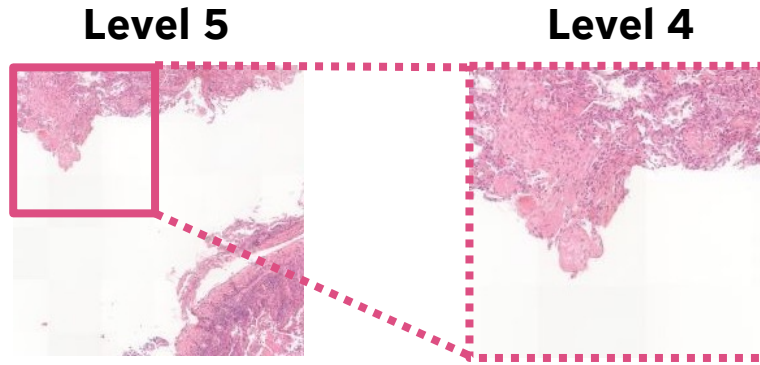
- Previous work in Deep Learning for WSI

- Efficient

[1] Li, C., Li, L., Jiang, H., Weng, K., Geng, Y., Li, L., ... & Wei, X. (2022). YOLOv6: A single-stage object detection framework for industrial applications.

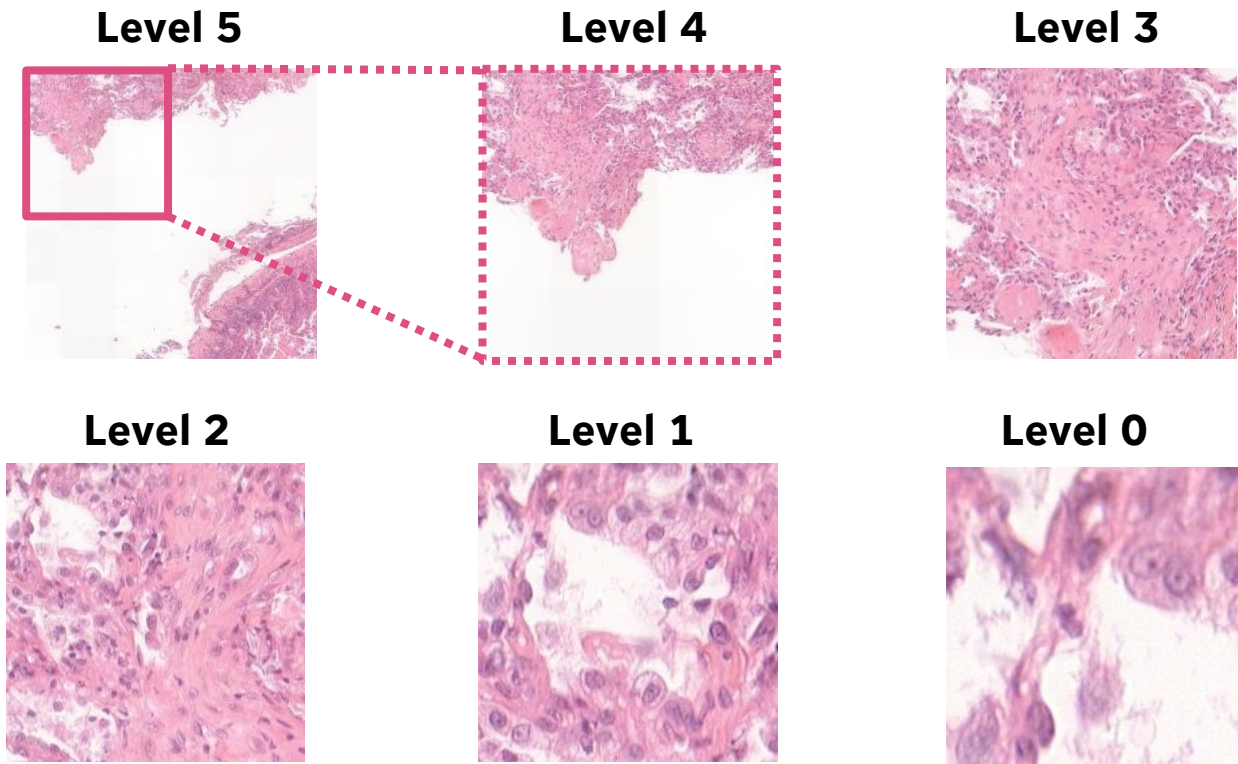# Choosing a Zoom Level: Precision and Context

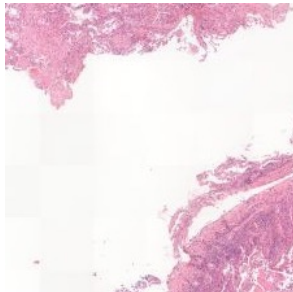**Level 5**

Choosing a Zoom Level: Precision and Context

Level 5

Level 4

Choosing a Zoom Level: Precision and Context

Level 5

Level 4
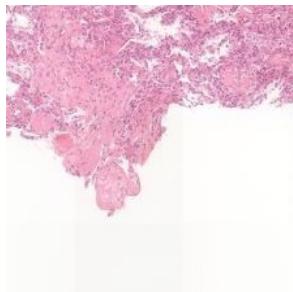

Level 3

Level 2

Level 1

Level 0

Choosing a Zoom Level: Precision and Context

Level 5
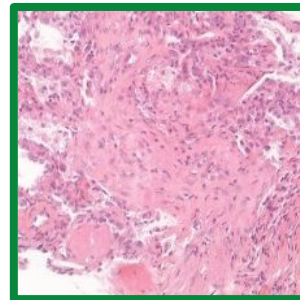
Level 4
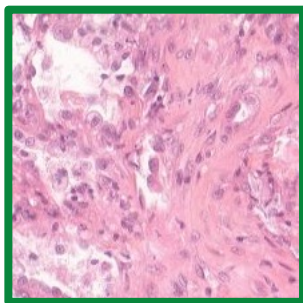
Level 3
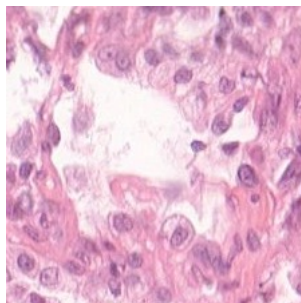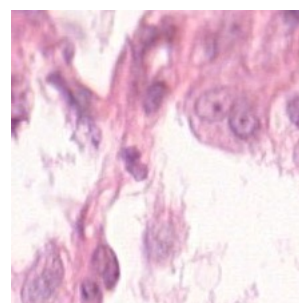

Level 2

Level 1

Level 0

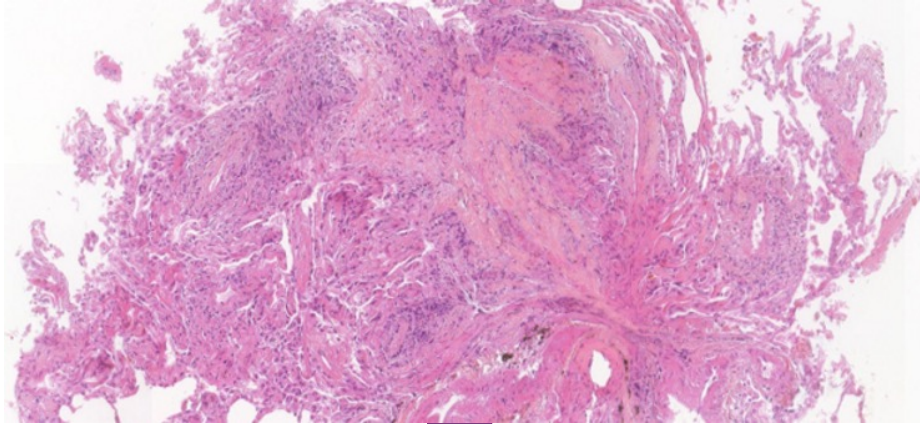# Patch Extraction

Image size at level 2:
20 000 x 50 000 pixels

Patch size for Machine Learning:
224 x 224 pixels

Generating Patches
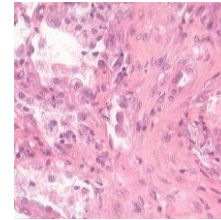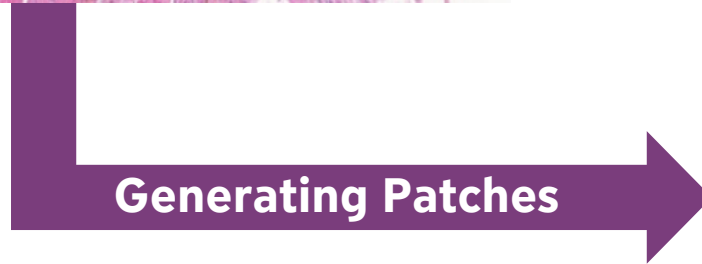
Level 2
20 000 patches
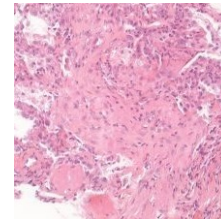
Level 3
5 000 patches

Patch Selection

Level 5: Is patch an artifact or background?

No

Level 4: Is patch an artifact or background?

No

Level 3: Is patch an artifact or background?

No

Patch selected

Patch Annotation

1. Select patch
2. Assign a **soft label**:

$$y_{\text{Bbox}} = \begin{cases} 0, & \text{if patch has no overlap with a lesion} \\ \text{gIoU}(\text{lesion}, \text{patch}), & \text{otherwise} \end{cases}$$

Example:
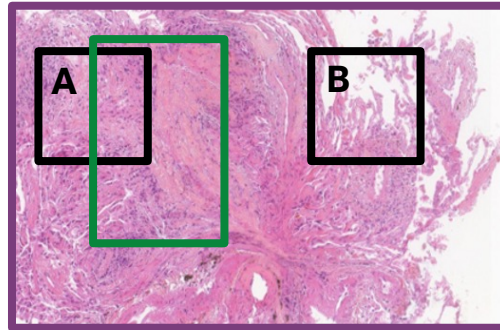
$$y_A \in \,]0, 1[$$
$$y_B = 0$$

Patch Annotation

1. Select patch
2. Assign a **soft label**
3. Balance the dataset

Training Dataset:

Randomly select patches to achieve a **2:1 ratio** (no overlap: overlap).

Model Training
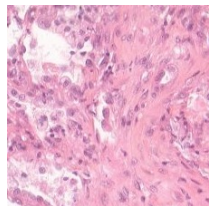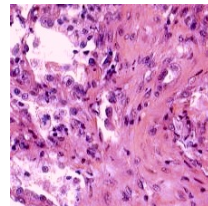## Patch Classification

Patch Preprocessing

1. Enhance the **contrast** and **standardize** Luminosity
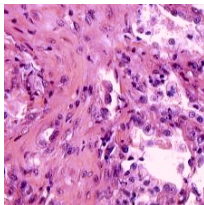

Original Patch

Pre-processed Patch

2. Data **augmentation**

Vertical/ Horizontal Flip
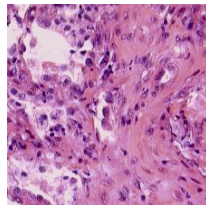
Color Jitter
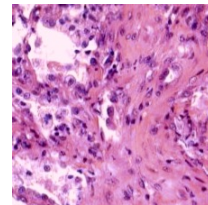
Gaussian Blur

Model Architecture

Tested pre-trained image classification models:

- Dinov2 [2],
- Swin [3]...

$\longrightarrow$ Selected the **Dinov2 small** model

- Open source model (🤗 **Hugging Face**)

- Reduced training time

Presence of Lesion

[2] Darcet, Timothée, et al. "Vision transformers need registers."
[3]. Liu, Ze, et al. "Swin transformer: Hierarchical vision transformer using shifted windows."
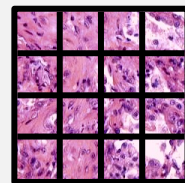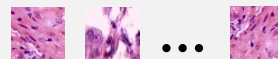
Implementing a Soft Focal Loss

Focal loss [4]: Loss first used in object detection to address the background/object class imbalance.

We use this loss with **soft labels:**
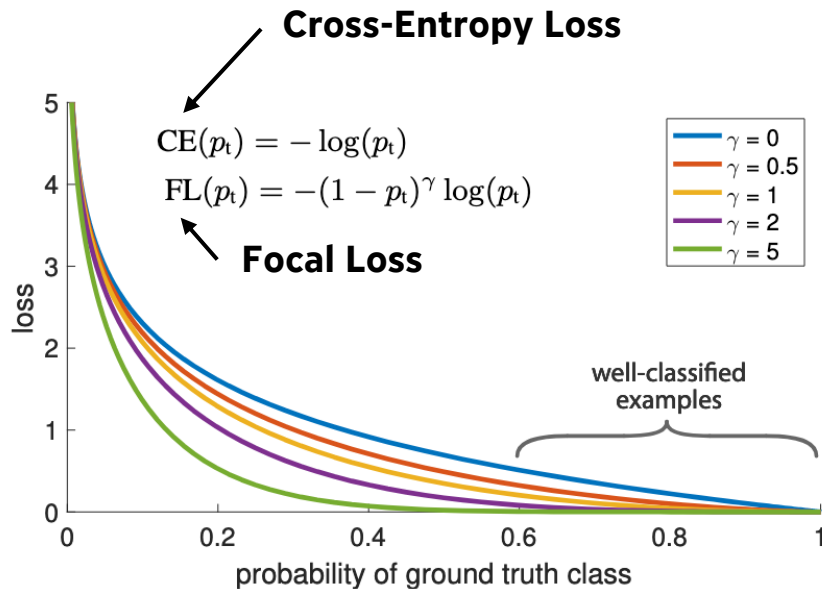

The <u>label</u> of a patch is the **overlap** between **patch** and **lesion.**

We **scale** the soft labels before computing the loss.

Cross-Entropy Loss

$$CE(p_t) = -\log(p_t)$$

$$FL(p_t) = -(1 - p_t)^\gamma \log(p_t)$$

Focal Loss

	$\gamma = 0$
	$\gamma = 0.5$
	$\gamma = 1$
	$\gamma = 2$
	$\gamma = 5$

well-classified examples

loss

probability of ground truth class

[4] Lin, T. "Focal Loss for Dense Object Detection."

Detection of Graft Rejection

Predicting Lesions: Higher Level

Level 3 Zoom

Extracting Overlapping patches

Patches

Predicting Level 3 model

Scores

0.23

0.56

...

0.31

Predicting Lesions: Higher Level

Level 3 Zoom → **Patches** → **Scores**

Extracting Overlapping patches

Predicting Level 3 model

0.23

0.56

...

0.31
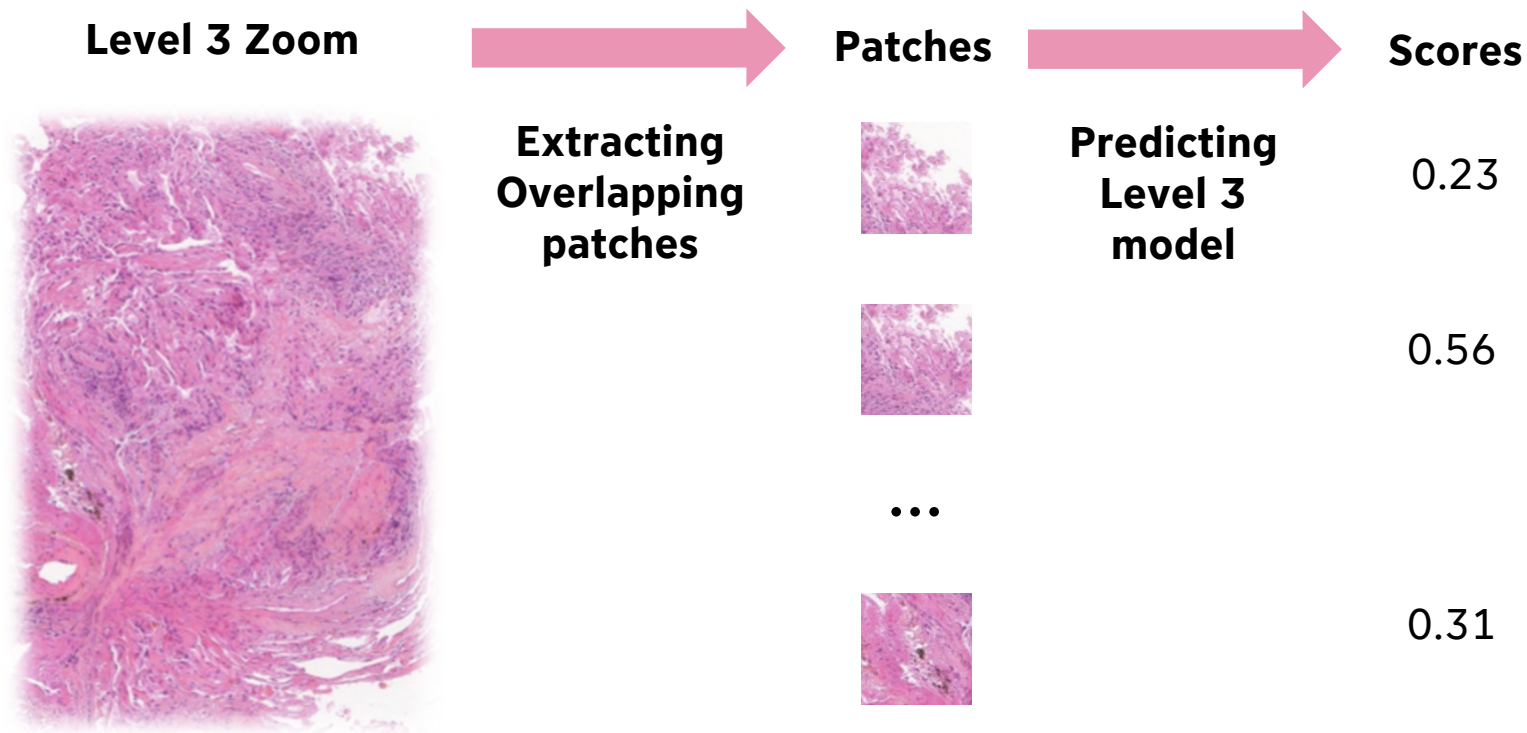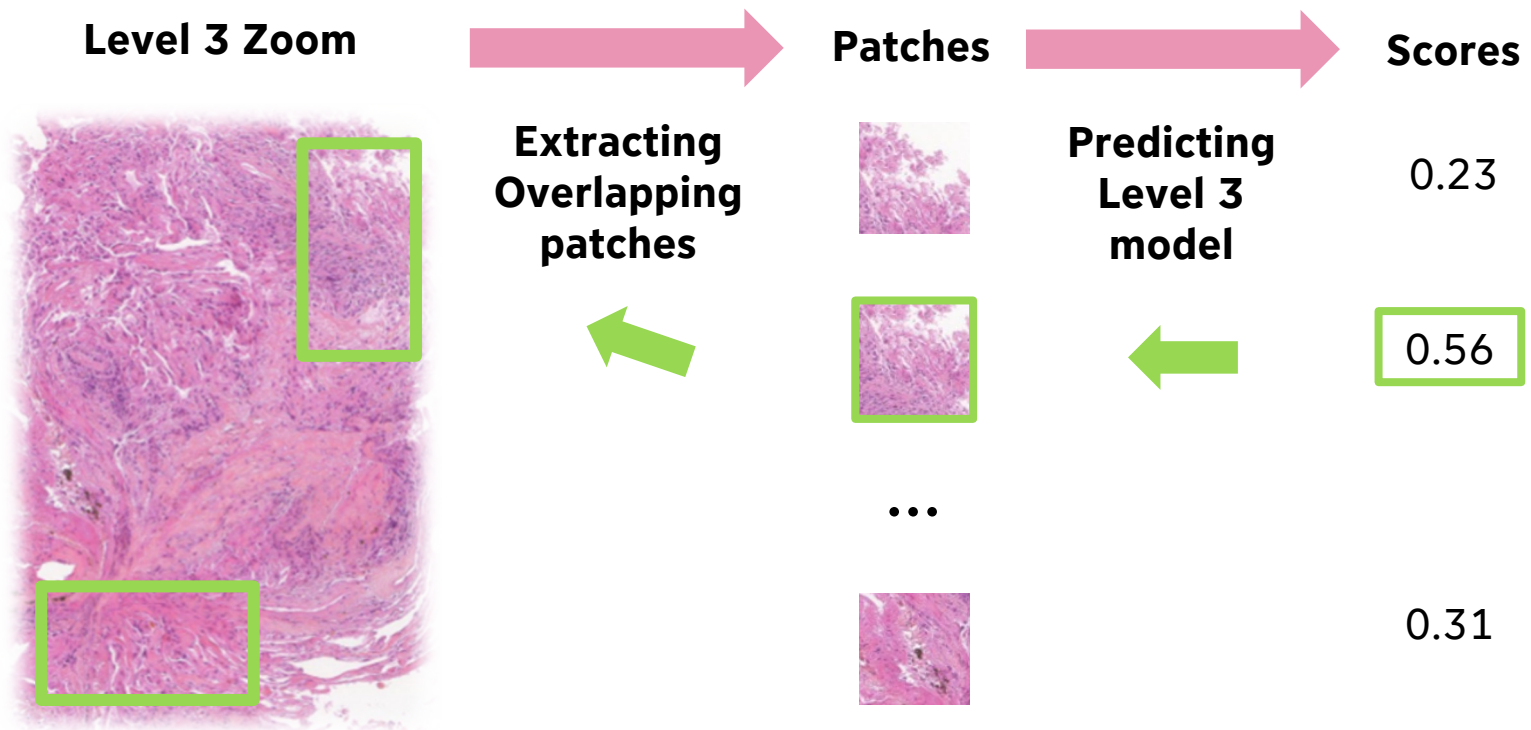
Predicting Lesions: Lower Level
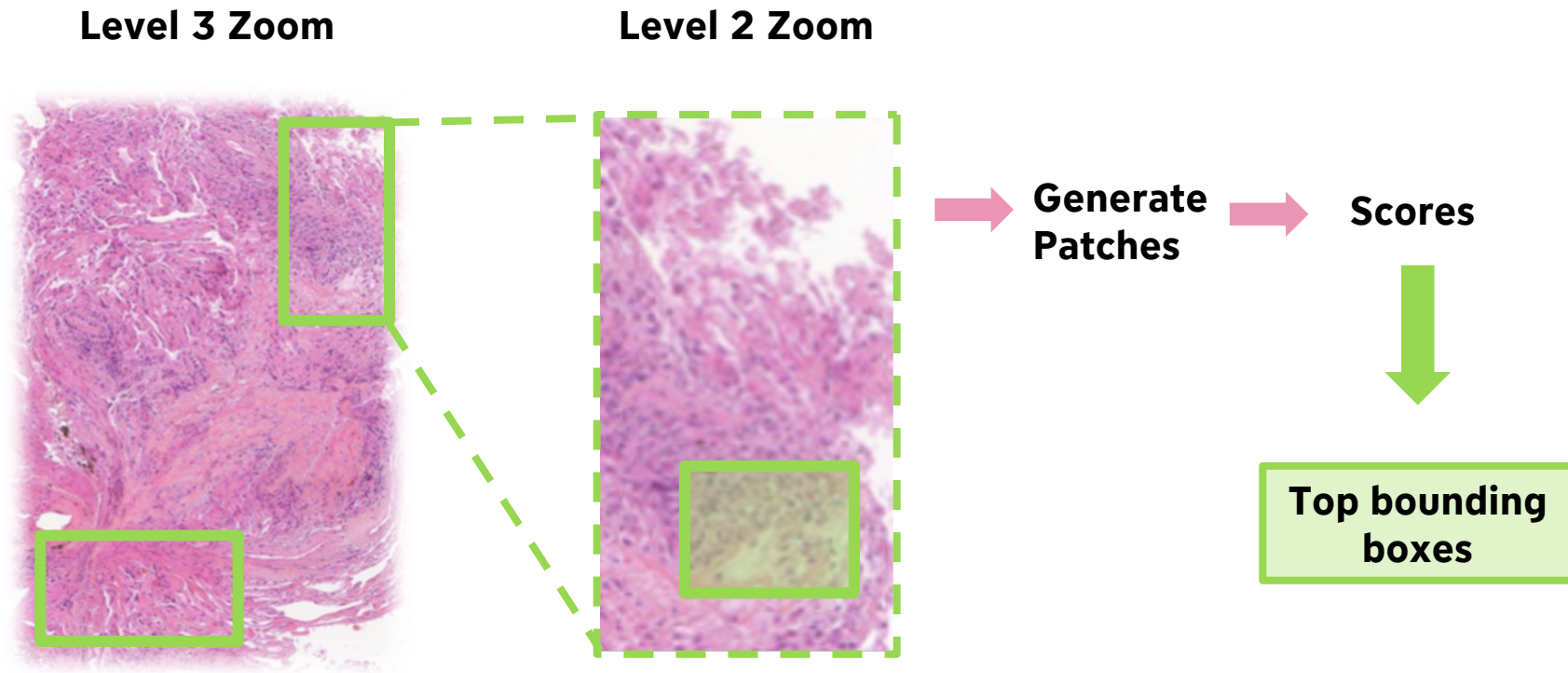
Level 3 Zoom

Level 2 Zoom

Generate Patches → **Scores**

Top bounding boxes

Results

Results

Public Leaderboard

Rank	Members	Team	Score
🥇	2 ⓘ	CVN	0.4122479325926966
🥈	2 ⓘ	MaD lab (team)	0.3778973169602485
🥉	1	Sheoran	0.3469621177771763
4	1	Kirill Brodt	0.28751367824832735
5	1	Amine Marzouki	0.26617662202389847

Private Leaderboard

Rank	Members	Team	Score
🥇	2 ⓘ	CVN	0.39785619771945163
🥈	2 ⓘ	MaD lab (team)	0.3260887998317052
🥉	1	Sheoran	0.2507181626600864
4	2 ⓘ	Raphaël Bourgade + MPWARE	0.24338232144947208
5	1	Raphael Kiminya	0.22056285013635285

Outlook

Medical Perspective: Exchange with clinical partners for feedback

Explaining Performances: Study the impact of various parameters

(image size, model size) through **ablation studies.**

Leverage the **non-annotated data** through self-supervised pre-training.

Implementation: Discuss translational possibilities

Timeline

2021	**2021- 2024**	**Summer 2024**	**November 2024**	**2025-**
Challenge selected	Dataset Creation	DigiLut Challenge	Results Presentation	Continuing collaboration

Thank you for your attention!