



B i a P y

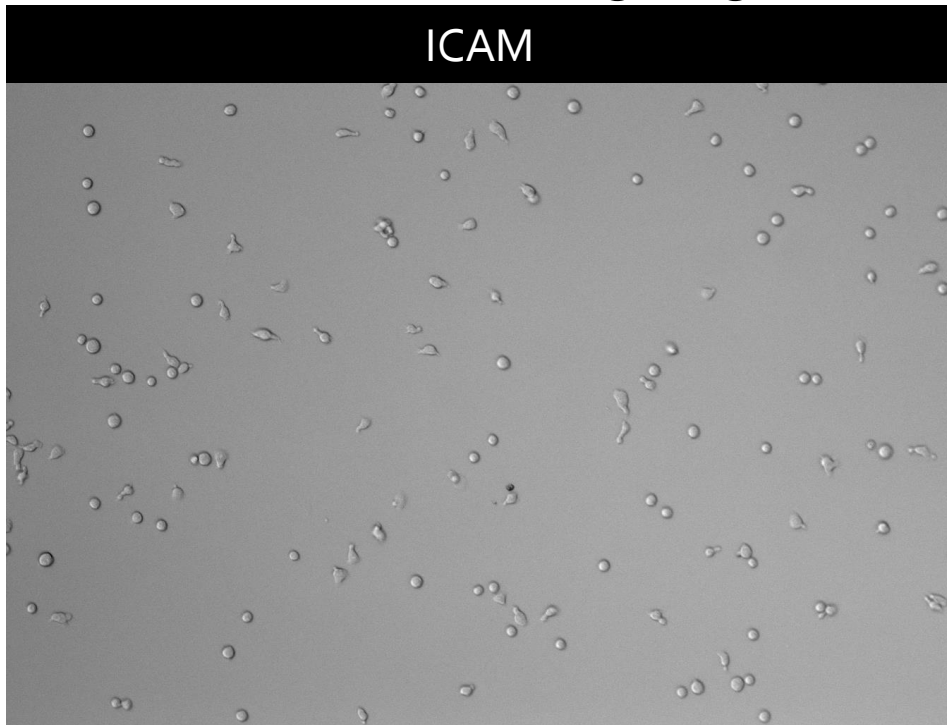
# DEEP LEARNING USING BIAPY

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Hands on training

# OUR TASK ON NEXT TWO DAYS

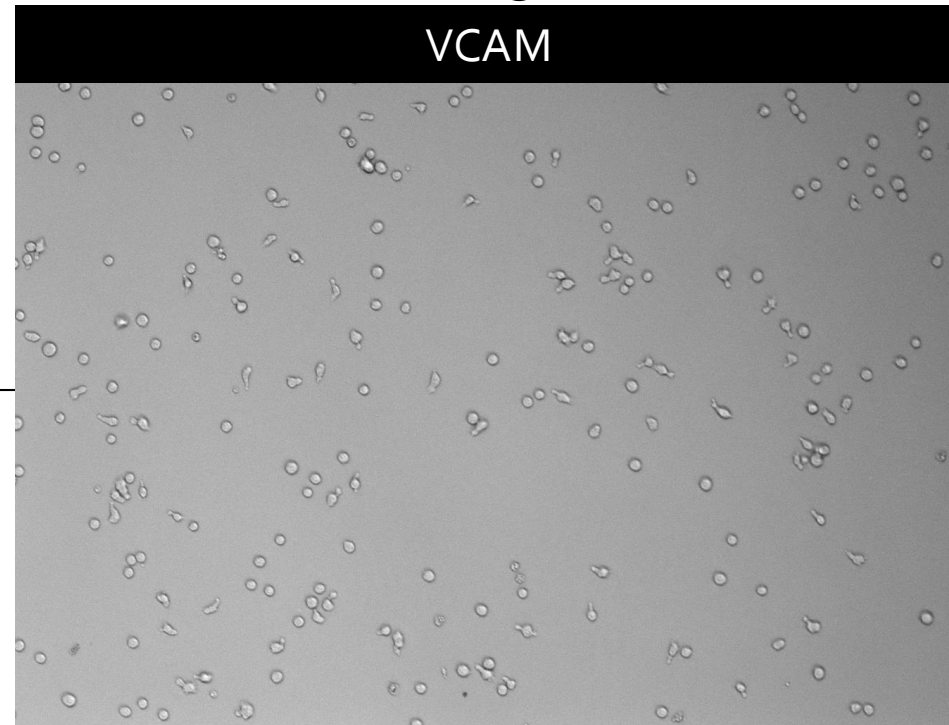
How does the coating on glass bottom dishes affect the migration of T-cells?



## ICAM-1 (Intercellular Adhesion Molecule-1):

Binds to **LFA-1**, an integrin expressed on T cells.

- Typically mediates **firm adhesion and rapid crawling**.
- Promotes **polarized morphology** and fast, exploratory migration.
- Often associated with surveillance in non-inflamed tissues.



## VCAM-1 (Vascular Cell Adhesion Molecule-1):

Binds to **VLA-4**, another integrin on T cells (also called  $\alpha_4\beta_1$  integrin).

- Often leads to **slower, more stable interactions**.
- Induces **different signaling cascades**, sometimes associated with T cell retention or transmigration.
- More prominently expressed in **inflamed endothelium**, guiding T cells into sites of inflammation.

# Steps for solving the task

Train a deep learning model to  
segment cells

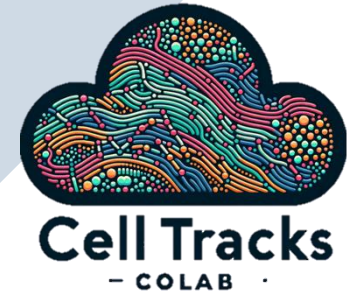


BiaPy

Cell tracking  
(tomorrow with Jean-Yves)



Track analysis  
(tomorrow with Laura)



# Steps for model training in BiaPy

Create  
training  
dataset

Upload  
data to G-  
drive

Install  
dependencies

Define  
paths to  
training  
and QC  
data

Train

Asses the  
quality of  
your model

Run  
predictions  
on unseen  
data



Or any  
other tool





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# How to create a training dataset for StarDist?

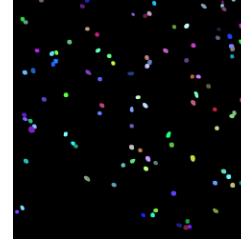
- Open Fiji – activate LOCI update site
- Restart Fiji
- Open your image to be annotated *Image1-T-cells*
- Select the Oval  or Freehand selection tool 
- Start drawing selections around each (yes each!) cell
- After every cell press t -> the selection will be stored to the ROI manager
- Repeat until all cells are in the ROI manager
- When done *Plugins > LOCI > ROI Map*
- Save the generated ROI map with the same title as the original image
- At the end you have one folder with the original images, another with the ROI maps

# Suggested folder structure for BiaPy

1-train

1-raw

2-label

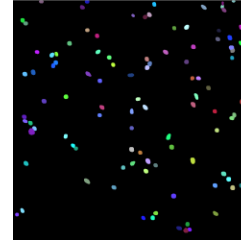


200 image pairs, 10 % for validation

2\_test

1-raw

2-label



10 QC image pairs

3\_model

4\_own\_data



Data to be segment

5\_own\_data\_results

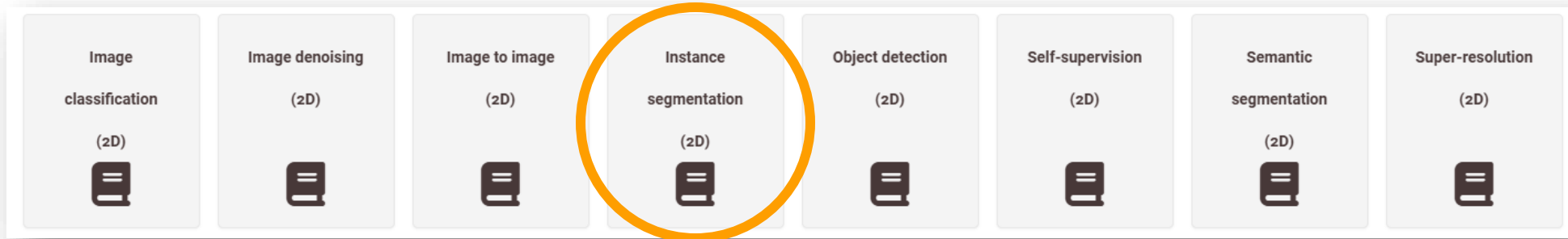
Your results will be here

# Do you all have Google drives?

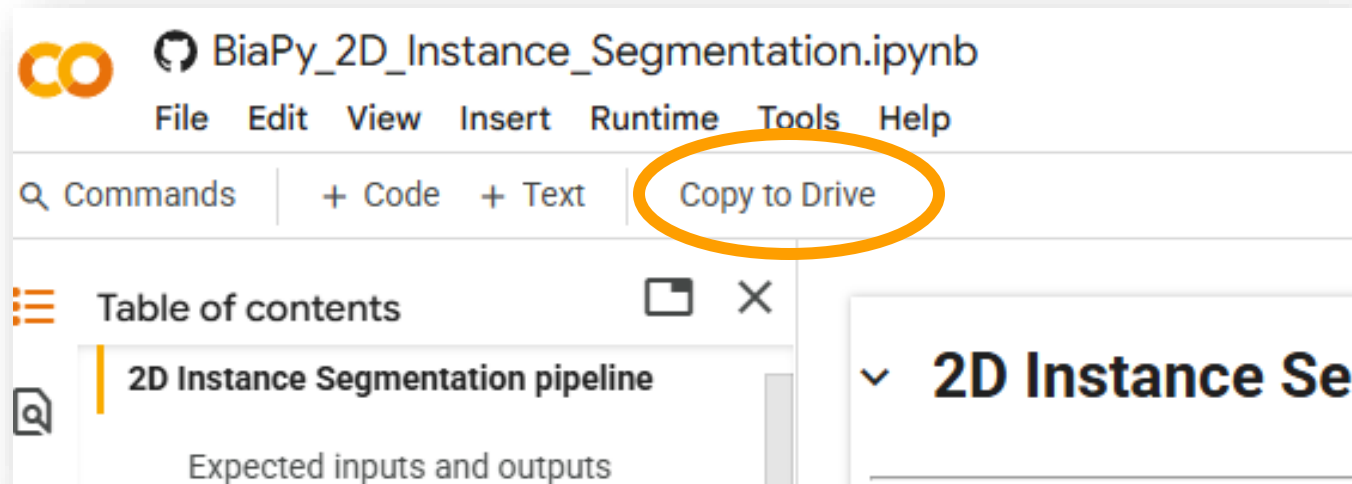
- Log in to your google account
- Make sure the workshop images are uploaded
- Using the same browser go to <https://biapyx.github.io/>

# Open the notebook

- Look for the notebook, called **Instance segmentation (2D)** and open it

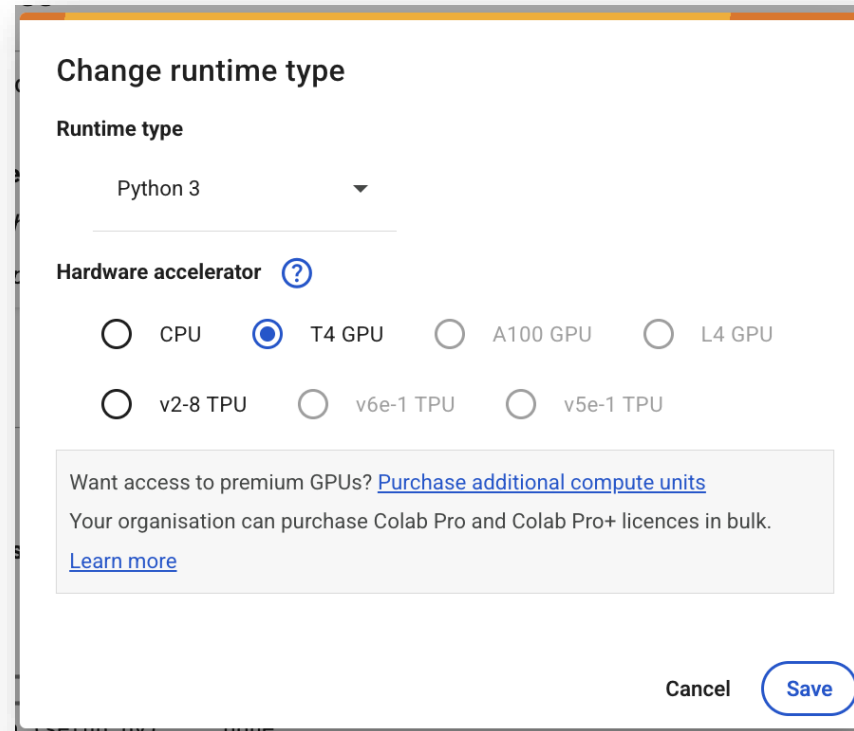
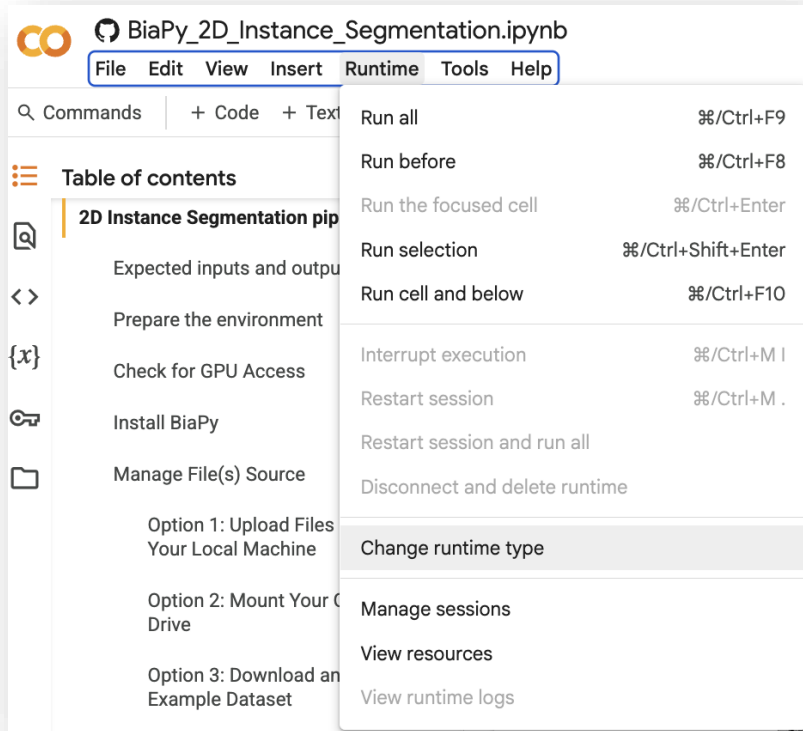


- Copy it to your drive and give it a name – close the original notebook





# Prepare the session



**Check for GPU access!!!**  
**Go to Runtime -> Change the Runtime type to T4 GPU**

▶ Play to reinstall Colab libraries so they are compatible with BiaPy

▶ Play to install BiaPy and its dependences

# Connect to Google drive and load data

## ▼ Manage File(s) Source

The input folder can be provided using three different options:

1. **Direct Upload:** Directly upload the desired folder.
2. **Google Drive:** Use a folder stored in your Google Drive.
3. **Sample Data:** Use a sample dataset provided by us.

## ▶ Play the cell to connect your Google Drive to Colab

- Click on the URL.
- Sign in your Google Account.
- Copy the authorization code.
- Enter the authorization code.
- Click on "Files" site on the right. Refresh the site. Your Google Drive folder should now be available here as

▶ Path to train raw images

```
train_data_path: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/1-train/1-raw"
```

Path to train label images

```
train_data_gt_path: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/1-train/2-label"
```

Path to test raw images

```
test_data_path: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/2_test/1-raw"
```

Path to test label images (optional)

```
test_data_gt_path: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/2_test/2-label"
```

Path to store the resulting images (it'll be created if not existing):

```
output_path: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/3_model"
```

Number of training raw images: 200  
Number of training label images: 200  
Number of test raw images: 10  
Number of test label images: 10

▶ Play to visualize some data samples

# Training parameters

▶ Name of the model:  
model\_name: " Pasteur\_100

Data management:  
test\_ground\_truth: ☒  
percentage\_validation: 10

Basic training parameters:  
input\_channels: 1  
number\_of\_epochs: 100  
patience: 100

Advanced training parameters:  
model\_architecture: U-Net  
batch\_size: 8  
patch\_size: 256  
optimizer: ADAMW  
initial\_learning\_rate: 0.0001  
problem\_representation: Binary mask + Contours  
learning\_rate\_scheduler: None  
aggressive\_data\_augmentation: ☐  
test\_time\_augmentation: ☐

**model\_name:** Use only my\_model -style, not my-model (Use "\_" not "-"). Do not use spaces in the name. Avoid using the name of an existing model as it will be overwritten.

**test\_ground\_truth:** Select to use test data ground truth to measure the performance of the model's result. If selected, test\_data\_gt\_path variable path set above will be used. Default value:

**percentage\_validation:** Input the percentage of your training dataset you want to use to validate the network during the training. Default value: 10

**number\_of\_epochs:** Input how many epochs (rounds) the network will be trained. For the example dataset, reasonable results can already be observed after 100 epochs. **Default value: 100**

**patience:** Input how many epochs you want to wait without the model improving its results in the validation set to stop training. Default value: 20

# Train the model



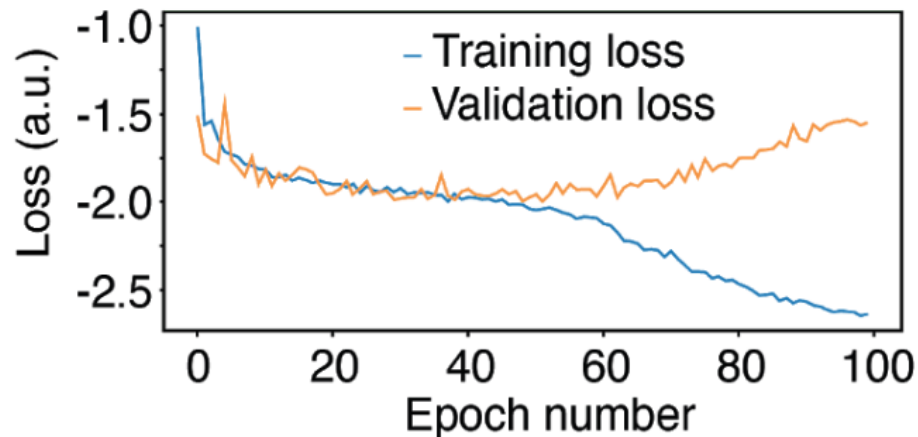
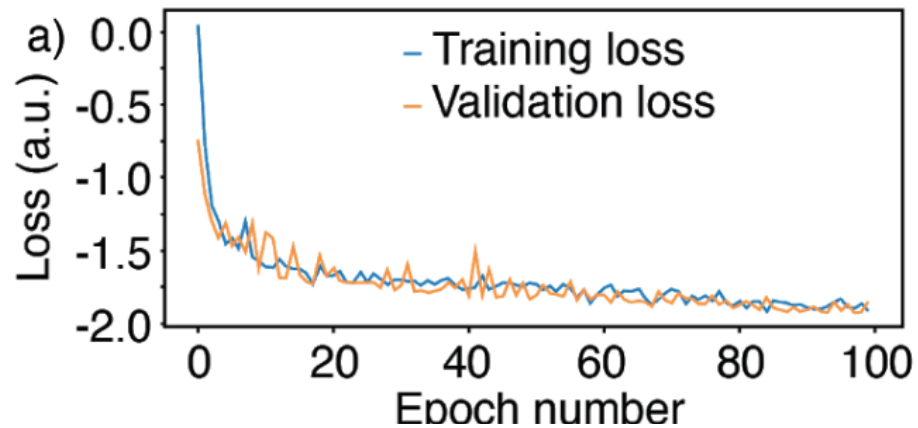
Play to train the model

**RUN QUALITY CONTROL ON  
YOUR MODEL**

# Quality Control1:

## Inspection of the loss function

- Train model for hundreds of EPOCH

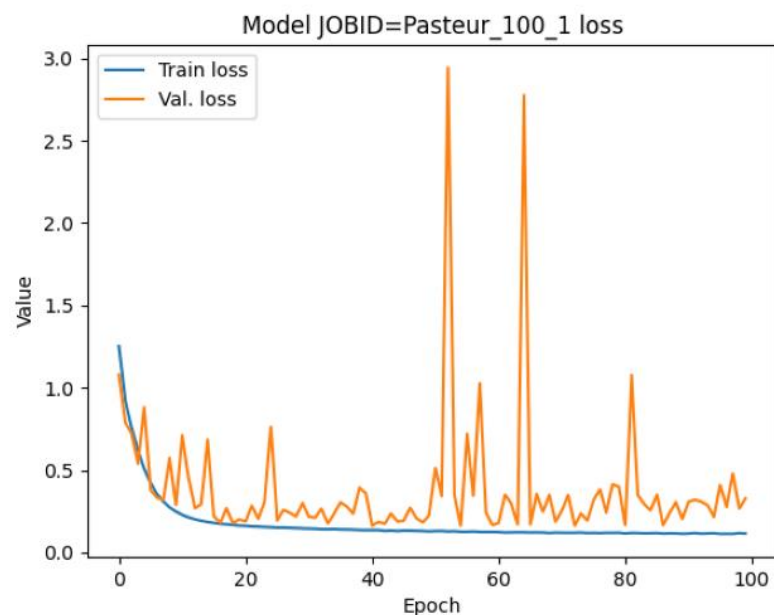


- Always evaluate the training progress, compare the training loss with the validation loss.
- **Training loss** describes an error value after each epoch for the difference between the model's prediction and its ground-truth target.
- **Validation loss** shows how well the network performs on the validation data.
- **Actions:**
  - Decreasing Training loss and Validation loss
    - train for more epocs
  - Curves are flattened out:
    - no more training is required
  - Validation loss increases while Training loss simultaneously decreases:
    - network is overfitting = remembering the exact patterns from the training data and no longer generalizes well to unseen data.
    - training dataset should be increased.

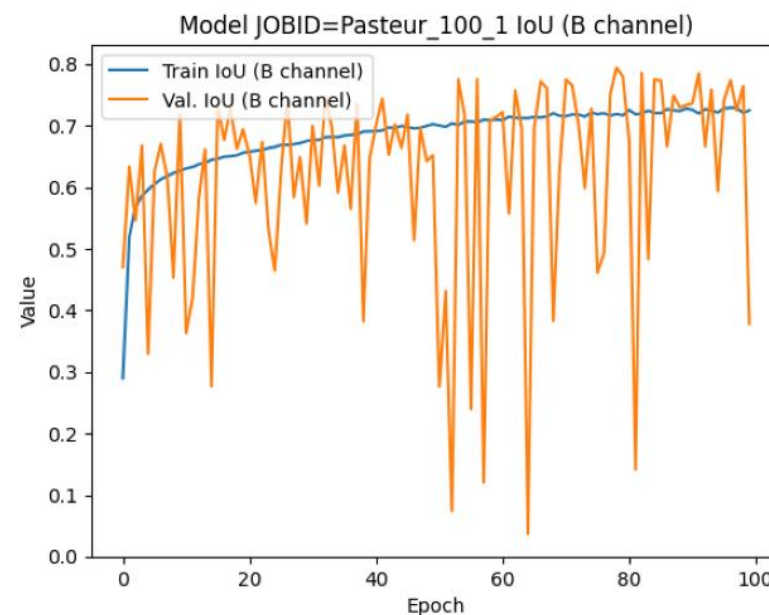
## ✓ Inspection of the Loss Function and the Intersection over Union (IoU)

- ▶ Play the cell to show a plot of training error vs. epoch number and IoU vs epoch number

Training error vs epoch number

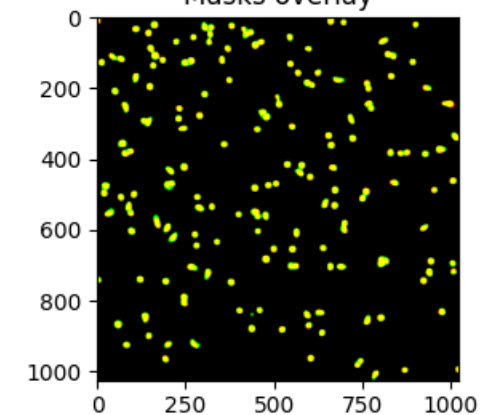
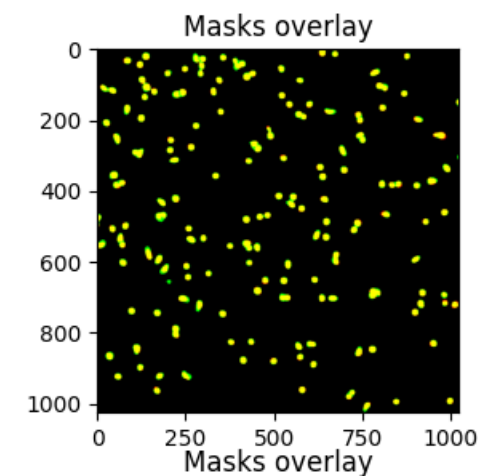
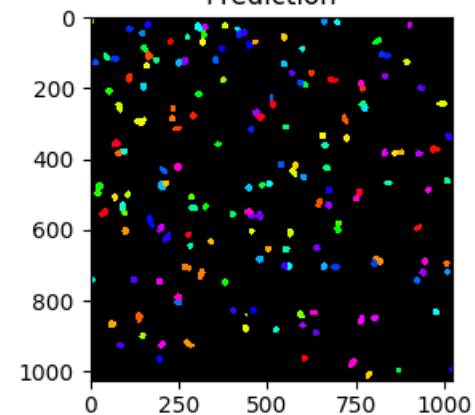
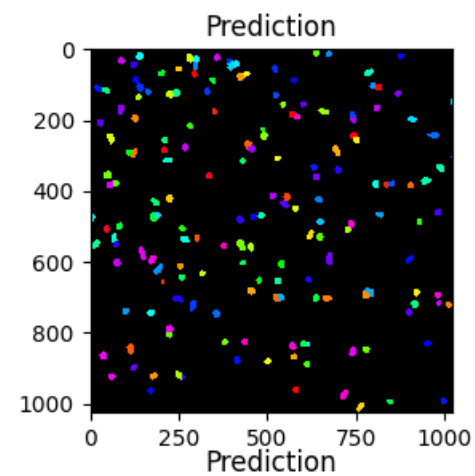
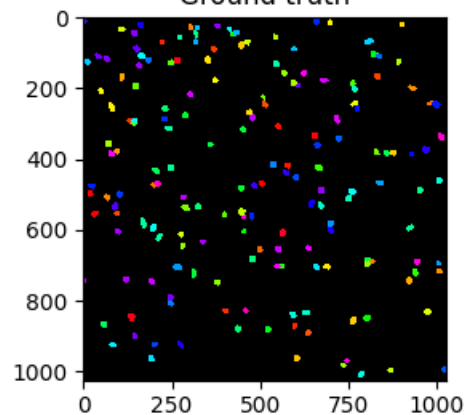
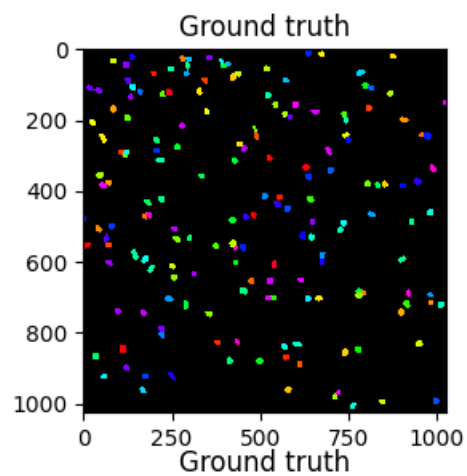
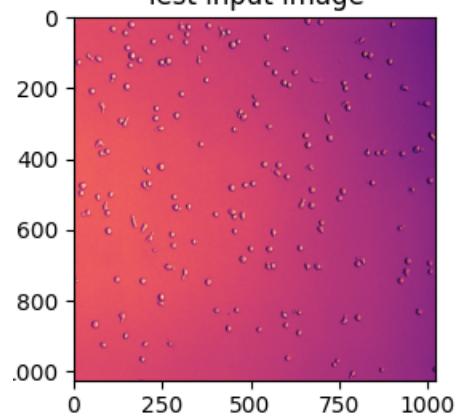
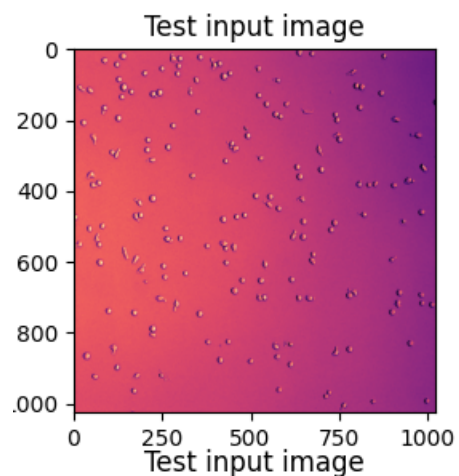


Intersection over Union (IoU) vs epoch number



# Quality Control2:

## Visual inspection





# Quality Control3:

## Error mapping and quality metrics estimation

GitHub



[Link to Quality control notebook](#)



### Quality control notebook for Pasteur 2025 course

#### ▶ Play the cell to connect your Google Drive to Colab

- Click on the URL.
- Sign in your Google Account.
- Copy the authorization code.
- Enter the authorization code.
- Click on "Files" site on the right. Refresh the site. Your Google Drive folder should now be available here as "drive".

[Show code](#)

#### ▶ Install dependencies

[Show code](#)

#### ▶ Load dependencies

[Show code](#)

#### ▶ Conduct QC on test data

```
gt_labels: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/2_test/2-label"
predicted_labels: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/3_model/Pasteur_100/results/Pasteur_100_1/per_image_instances"
QC_folder: "/content/gdrive/MyDrive/Pasteur_Image_analysis_course_2025_BiaPy/5_own_data_results/Pasteur_100/QC"
```

[Show code](#)

# Quality Control3:

## Error mapping and quality metrics estimation

image name	Prediction v. GT Intersection over Union	false positive	true positive	false negative	precision	recall	accuracy	f1 score	n_true	n_pred	mean_true_ score	mean_matched_ d_score	panoptic _quality
Training_source _ICAM 1-1.tif	0.89414007	2	153	2	0.987096	0.98709	0.974522	0.987096	155	155	0.873075	0.884487	0.873075

IoU: percent overlap between the target mask and your prediction output. **The closer to 1, the better the performance.** This metric can be used to assess the quality of your model to accurately predict nuclei. (whole image)

- “true positive” = When a segmented object has an IoU above 0.5 (compared to the corresponding ground truth)
- “false positive” = “n\_pred” - “true positive”
- “false negative” = “n\_true” - “true positive”

The mean\_matched\_score is the mean IoUs of matched true positives.

f1 score =  $2 * \frac{\text{Area of Overlap}}{\text{total number of pixels in both images}}$

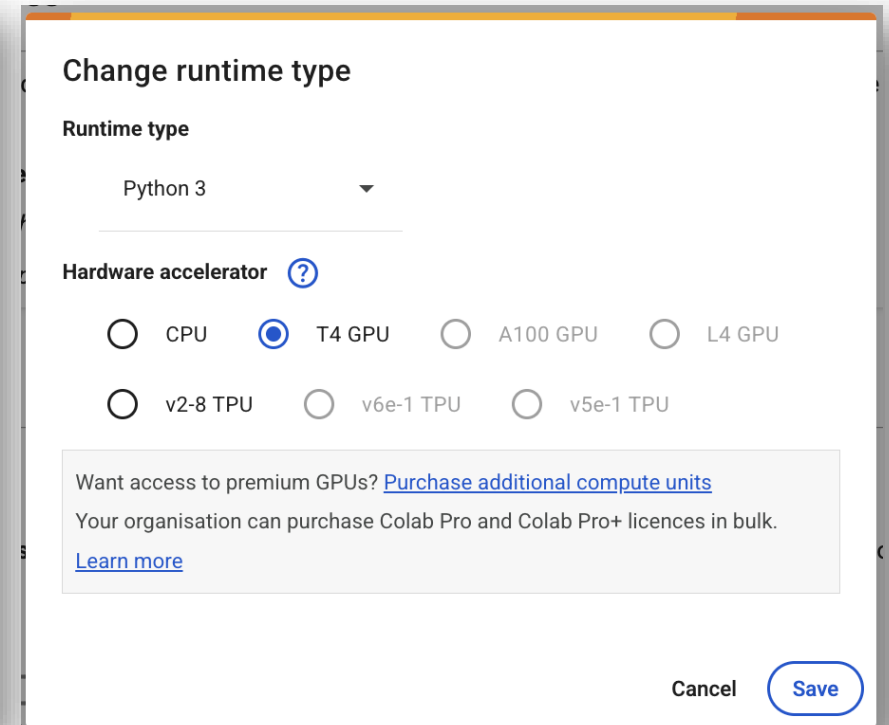
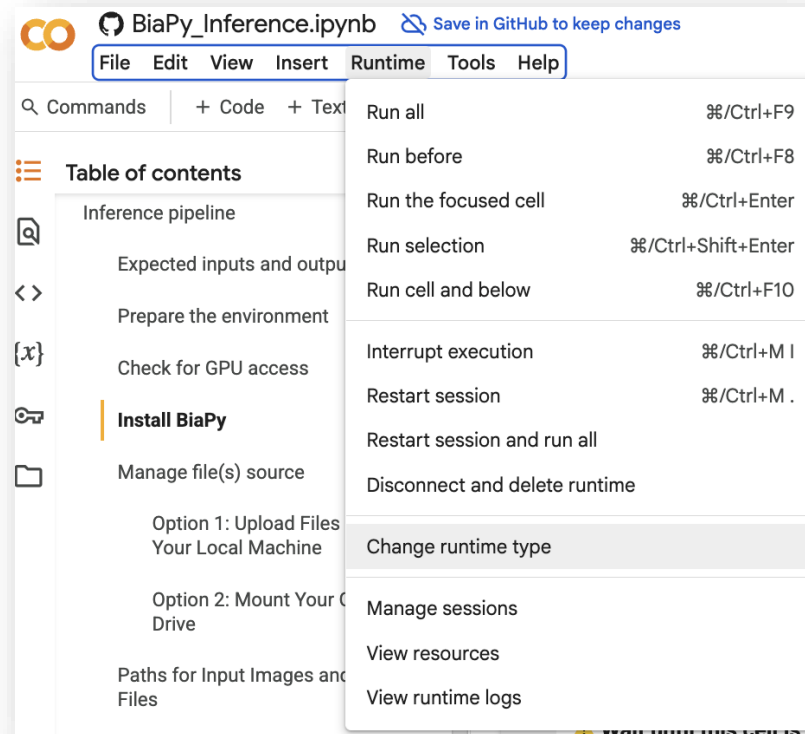
# Choose a model you want to use for unseen data

- Your own model
- Pasteur\_100

# Apply to your own data

Using the same browser  
go to

<https://biapyx.github.io/>



**Check for GPU access!!!**

**Go to Runtime -> Change the Runtime type to T4 GPU**

# Working with timelapse data

## ✓ Optional: Converting 3D data into 2D

Optionally, you can use this cell to convert your 3D images or videos into 2D images by extracting individual slices or frames. This enables compatibility with a trained 2D model. If this cell is run the paths to these new data will be used automatically.

▶ Path to store the 2D images generated from existing 3D

output\_2D\_slice\_folder: "/content/3D\_image\_slices"

Path to store the 2D ground truth images generated from existing 3D (if exists)

output\_gt\_2D\_slice\_folder: "/content/3D\_gt\_image\_slices"

▶ Play to generate 2D images from 3D

## ✓ Optional: Converting 2D slices into 3D again

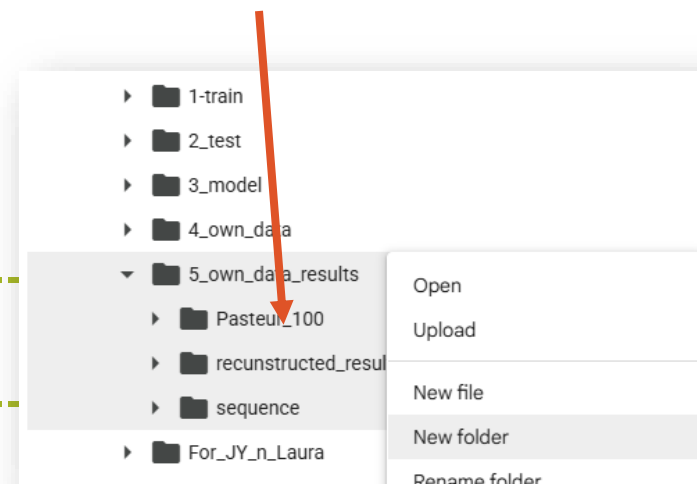
If you used the optional cell above to generate 2D images from 3D data, you can use this cell to reassemble the predicted 2D slices back into the original 3D image.

▶ Path to store the reconstructed 3D images:

reconstructed\_stack\_folder: "/content/reconstructed\_3D\_stacks"

▶ Play to generate 2D images from 3D

Create two new folders inside the 5\_own\_data\_results folder\_  
- sequence  
- reconstructed\_results





B i a P y

**AND WE ARE  
DONE 😊**

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