



# ADVANCEMENTS ON AERIAL ROBOTIC SYSTEMS AND SENSOR TECHNOLOGIES FOR FUTURE HEP DETECTORS



**Presenter:**

Kelvin Chan

**Supervisors:**

Francesco Mazzei,  
Paolo Francesco Scaramuzzino,  
Luca Bernardi,  
Corrado Gargiulo

# About Me:

Education: Hong Kong University of Science and Technology

Major: Physics

## Other Experience:

- HKUST Robotics team leader
- One year internship at Hong Kong Observatory







# About My Group:

Project: EP-R&D WP4.2 Robotics for Detectors

Main Goal:

Automate tasks like **installation, inspection, disconnection and maintenance** of detectors using robots

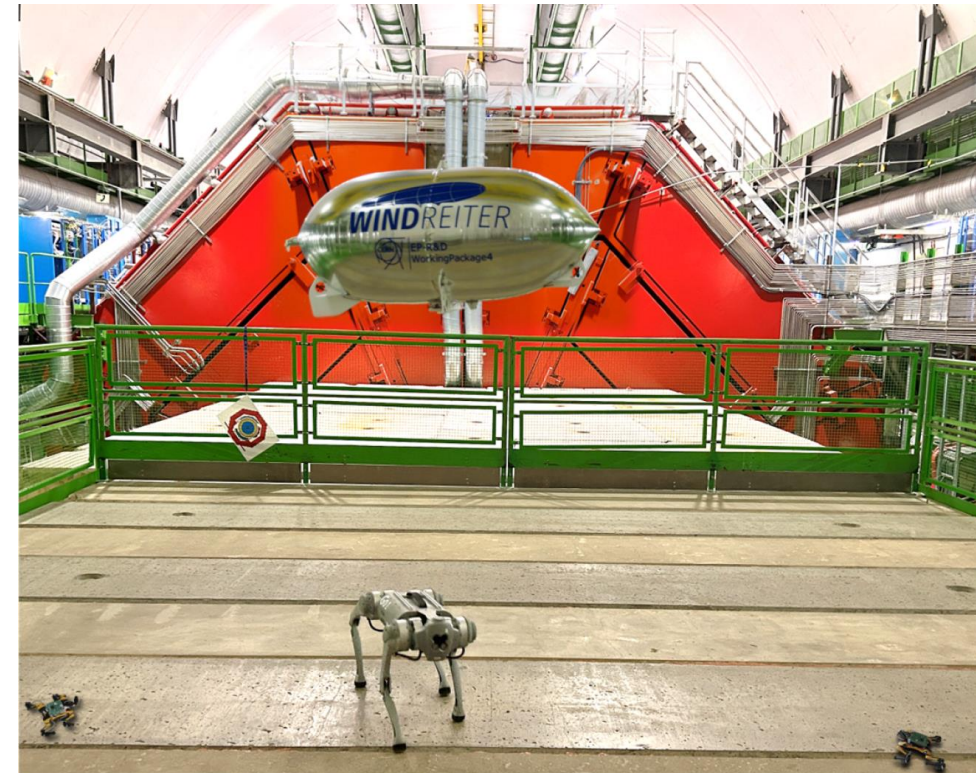
Challenges:

High **radiation** and **magnetic** field environments

Solutions:

**Aerial Robots Blimps (my project)**

Legged Robots



# About My Project:

## Project: Aerial Robot (Blimp) development

### What the group is working on:

1. Virtual environment for visualization of the Blimp dynamics and control (Francesco)
2. Camera placement optimization inside the cavern (Paolo)
3. Payload integration within the Blimp sensor bay

### What I did during the summer project:

1. Development of a camera-based detection and localization system of the Blimp
2. Onboard integration of a radiation detector

# Rundown:

## Blimp localization system:

- Background Introduction
- Object detection and YOLO
- Working flow
- Results and discussion
- Localization method
- Future developments

## Onboard radiation monitoring with MiniPIX TPX3 detector

- Background Introduction
- Onboard communication
- Radiation dose
- Future developments



# BLIMP LOCALIZATION SYSTEM





## Main Goal:

- Locate the **real-time position** of the Blimp in motion

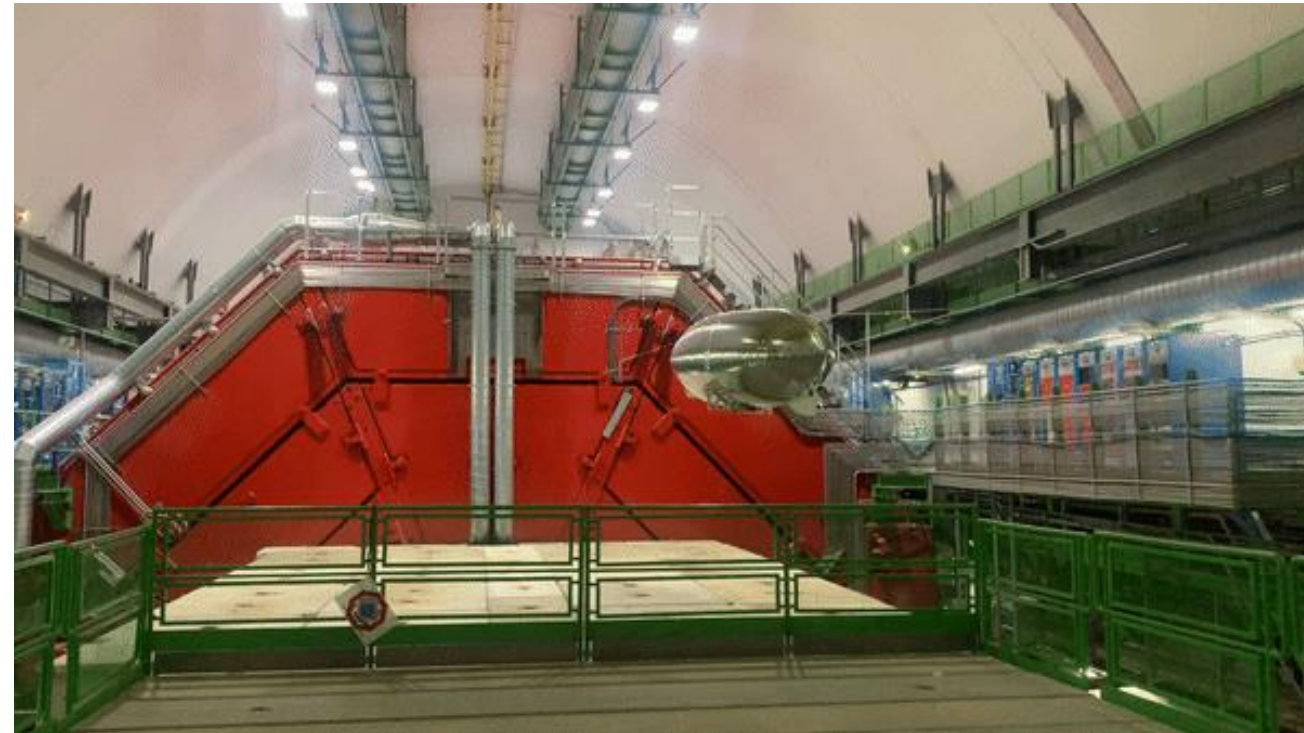
## Method:

- Install **webcams** inside the **detector cavern**
- Use a camera-based detection and localization system to:
  - **Minimize** radiation & magnetic **interferences**
  - **Minimize** Blimp **weight** (**No additional hardware** is required on the Blimp)

## Working Principle of a camera-based Localization System:

In each video frame captured by the webcams, a **Machine Learning Model**:

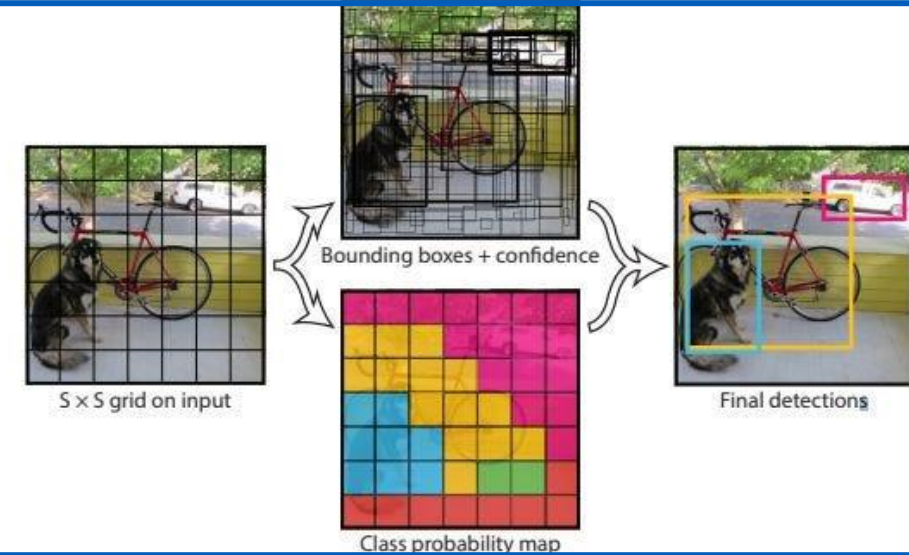
1. identifies in real time the Blimp
2. creates bounding boxes around each detected Blimp
3. computes the x-y position of the center of the bounding box
4. calculates the 3D position using information coming from multiple views



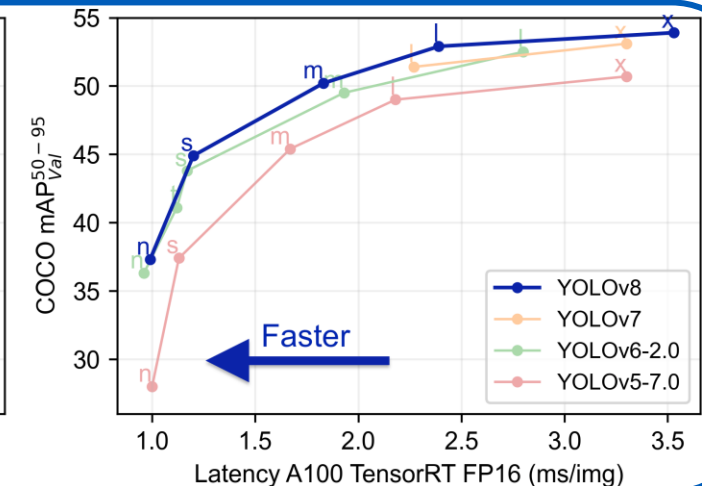
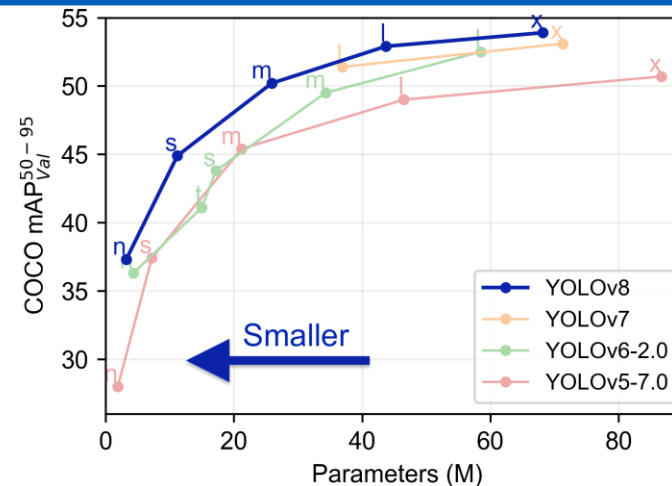


## You Only Look Once (YOLO):

- Deep learning algorithm for object detection
- Regression problem [1]:
  - ➔ bounding boxes and probabilities from a single image
- Exceptional speed and accuracy balance:
  - ➔ Very useful for real-time detections



- YOLO v8 with respect to previous versions [2]:
  - ➔ Reduced latency
  - ➔ Same accuracy with less parameters




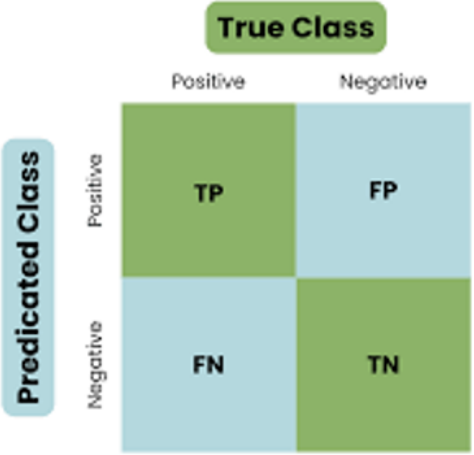
[1] Redmon, J., Divvala, S., Girshick, R., Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection.

[2] Terven, J., Diana-Margarita Cordova-Esparza, Julio-Alejandro Romero-Gonzalez. (2023). A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS. Machine Learning and Knowledge Extraction





Object Detection Metrics:

Intersection over Union	Confusion Matrix	Precision	Recall	F1 score
$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$ 		$Precision = \frac{TP}{TP + FP}$	$Recall = \frac{TP}{TP + FN}$	$F1 = \frac{precision * recall}{precision + recall}$
<p>Mismatch between the bounding box labelled by the developer and the bounding box identified by the detection model</p>	<p>Represents the results of model predictions</p>	<p>The percentage of correct predictions (how accurate the model is)</p>	<p>How well the model finds all positive (objects)</p>	<p>A measure that takes both precision and recall in account</p>
<p>TP: True Positive, FP: False Positive, TN: True Negative, FN: False Negative</p>				



## Working flow:

- **Dataset Preparation:** Label Studio (Best) / Roboflow / Labelling
- **Model Training:** YOLOv8 & Pycharm (Python Script)
- **Model deploy:** OpenCV & Pycharm (Python Script)
- **Blimp localization system**-> evaluate the performance of the detection model



[https://github.com/Kelvinchan324/CERN\\_blimp\\_detection](https://github.com/Kelvinchan324/CERN_blimp_detection)

Refer to GitHub page for further details and code



**DATASETS**

Label & Source

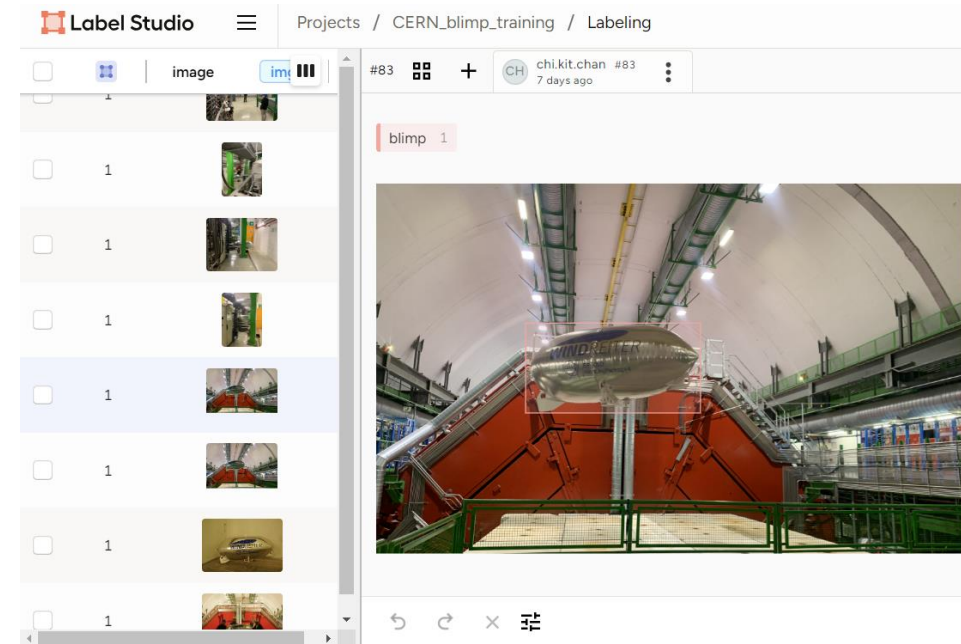
 roboflow

 Label Studio

 LabelImg

### Dataset Preparation:

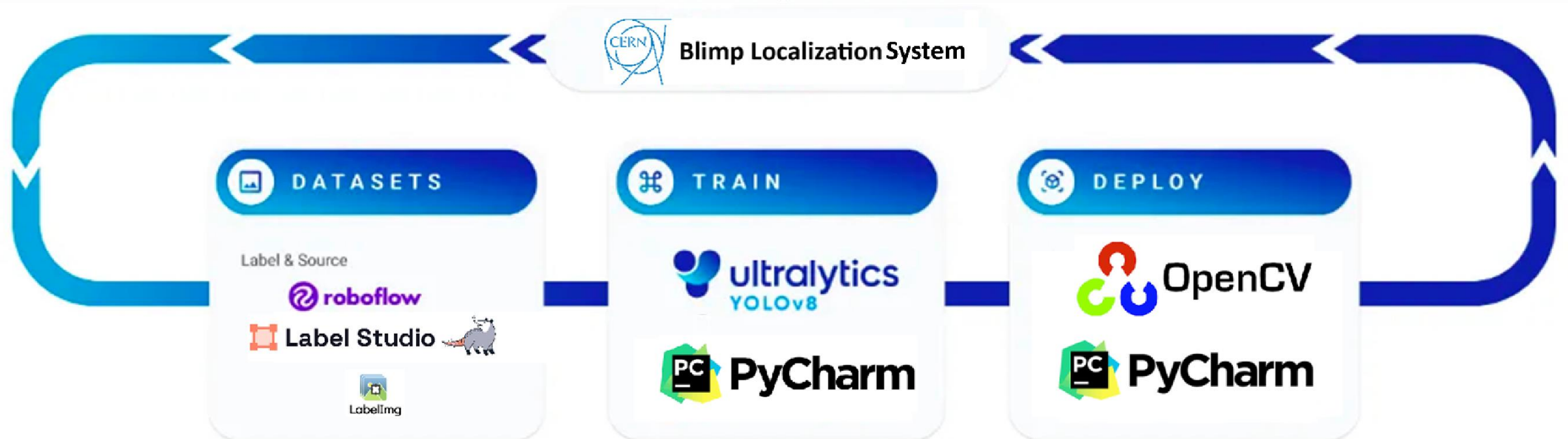
1. Separate dataset of images into three groups  
→ Training, validation and testing
2. Identify Blimps on images with labelling tools



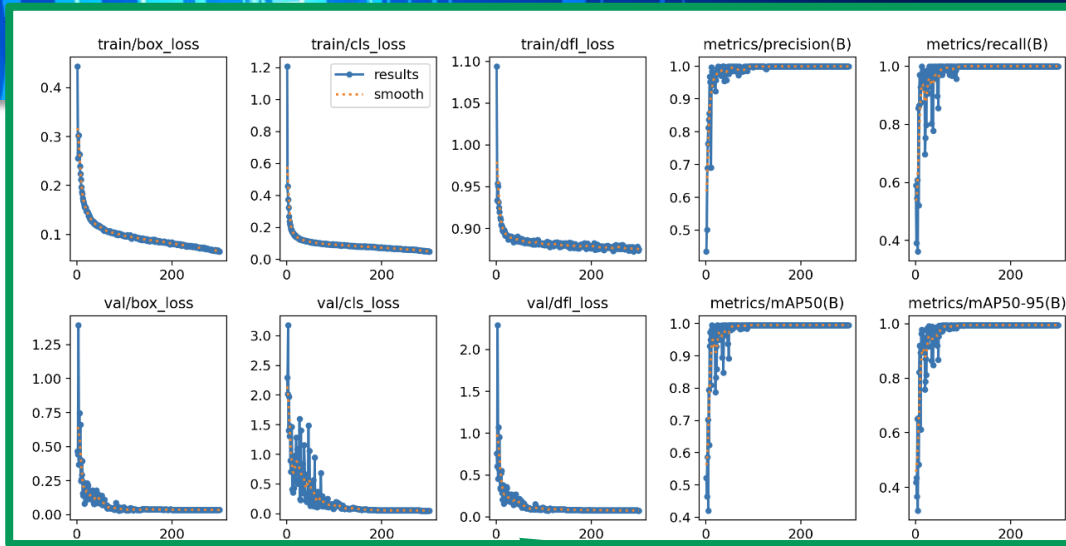
Number of photos used for different models

Training Object	Model Version	Training	Validation	Testing	Total
Generic Blimps	20240731-r	5595	69	230	5894
	20240731-py	5595	69	230	5894
Specific Blimp	20240802-py	12	1	1	14
	20240806-py	184	30	10	224
	20240807-py	287	70	24	381
	20240808-py	600	100	54	754





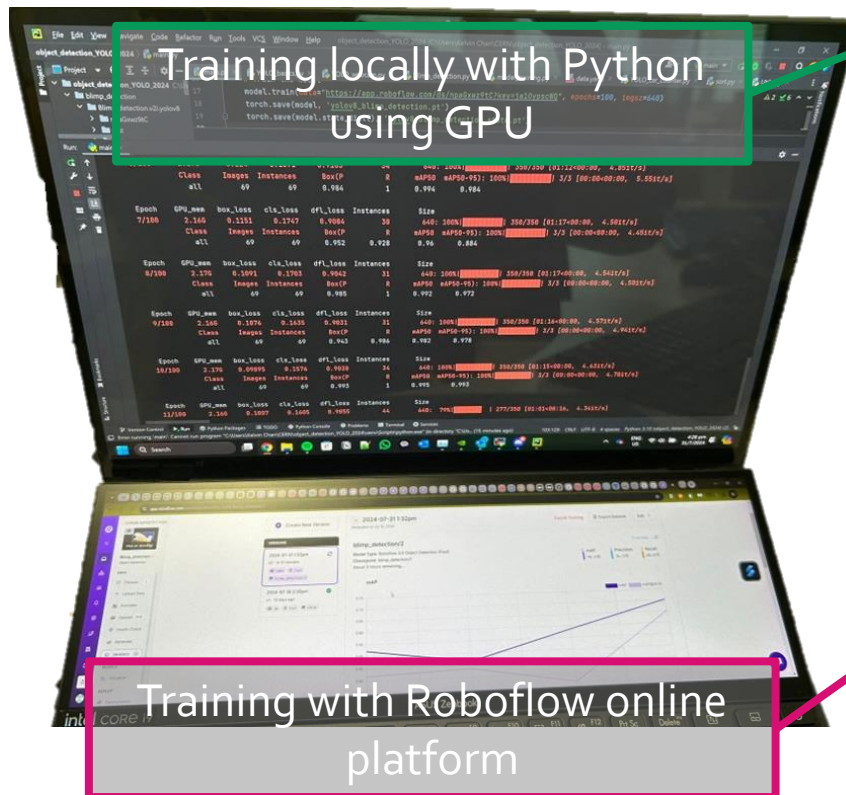
# MODEL TRAINING



## Model Training:

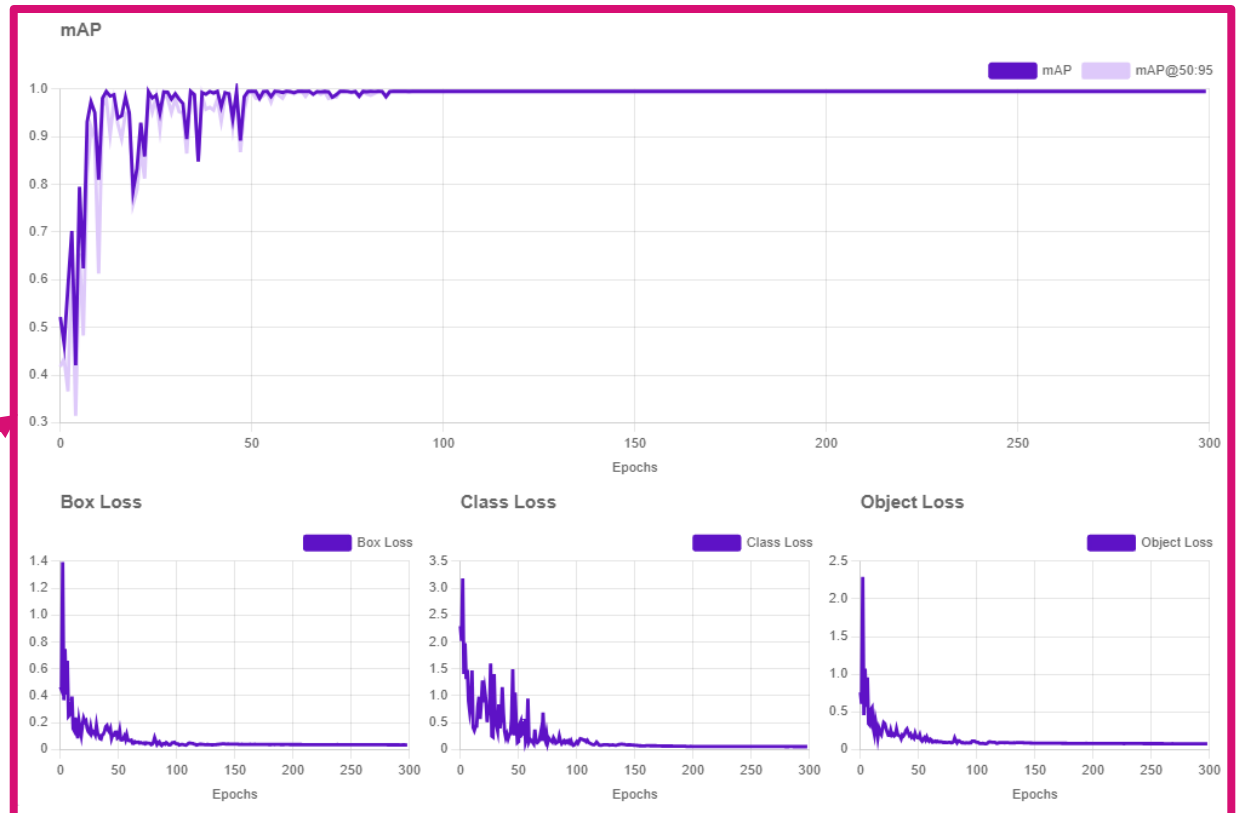
1. First model trained with Roboflow
2. Latest versions trained locally with YOLO with self-written Python scripts

Able to check training status in both



Training locally with Python using GPU

Training with Roboflow online platform





EP R&amp;D



Blimp Localization System



DATASETS

Label &amp; Source

Label Studio 

Labelimg



TRAIN

ultralytics  
YOLOv8

PyCharm



DEPLOY



OpenCV



PyCharm

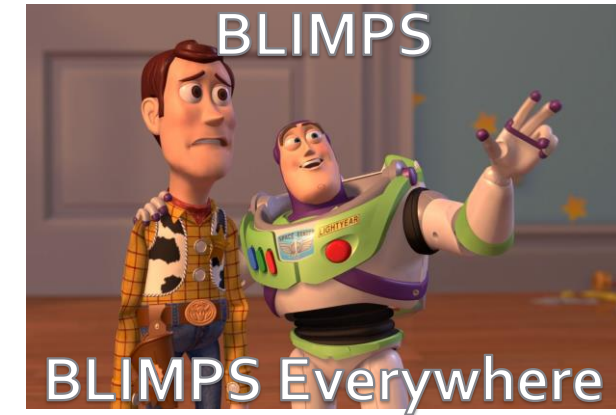




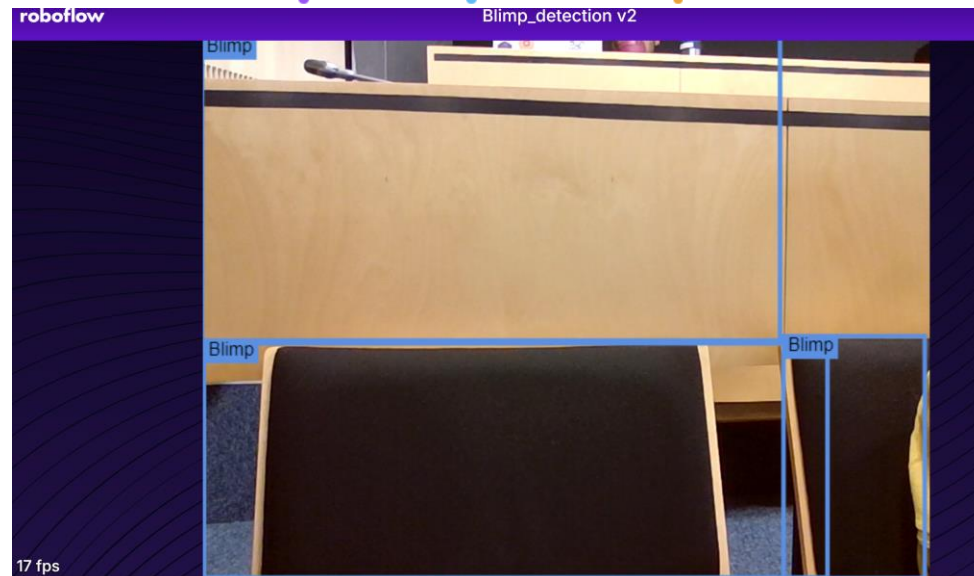
### Results and discussions:

Models "20240731-r" (Roboflow) & "20240731-py" (Local)

- Same dataset: around **6000** generic Blimp images
- Performance: **Bad** although metrics look good
- Images are **too generic** so that the model mistakenly recognizes **everything as a Blimp**



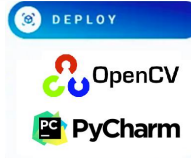
mAP 99.5% Precision 99.9% Recall 100.0%



Model "20240731-r" (Roboflow)



Model "20240731-py" (Local)



### Results and discussions:

Model "20240802-py"

- Dataset: 14 specific Blimp images in ALICE cavern
- Performance: **Acceptable**
- **HIGH** Precision, **LOW** Recall, **LOW** F1

Model can recognize the Blimp but may lose track

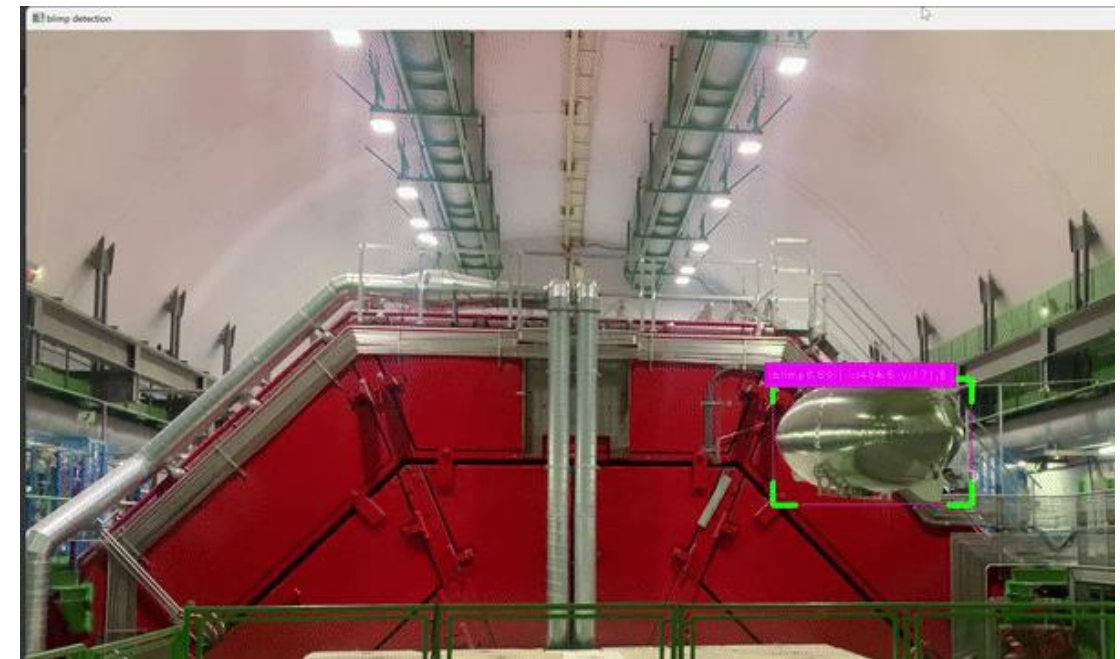


Model "20240802-py"

Model "20240806-py"

- Dataset: around 200 specific Blimp images in ALICE cavern
- Performance: **Good**
- **HIGH** Precision, **Acceptable** Recall, **Acceptable** F1

Model can recognize the Blimp in 2022 videos with no issues



Model "20240806-py"



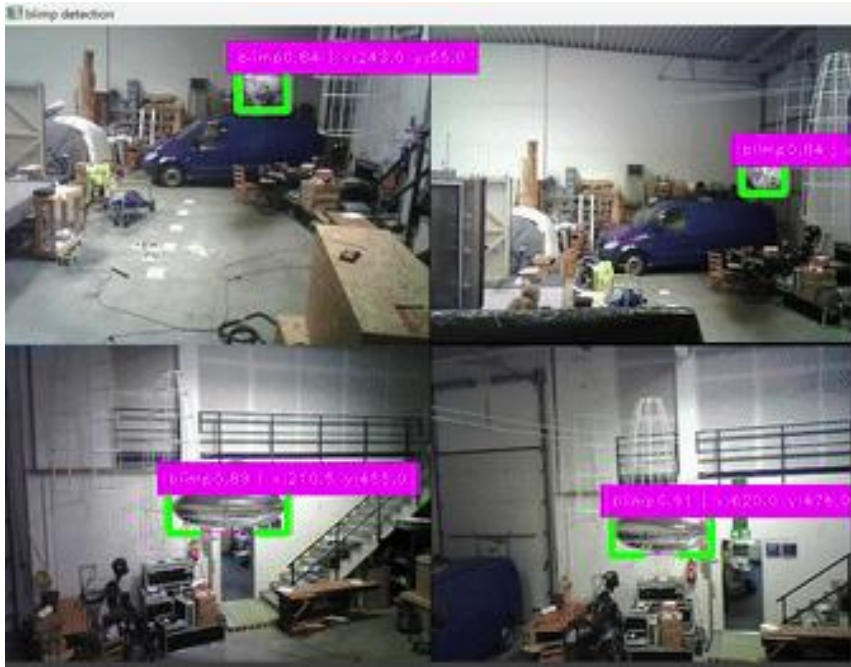


## Results and discussions:

### Model "20240807-py"

- Dataset: 400 specific Blimp images
- Performance: **Good**
- **HIGH** Precision, **HIGH** Recall, **HIGH** F1

Model can recognize the Blimp with different background

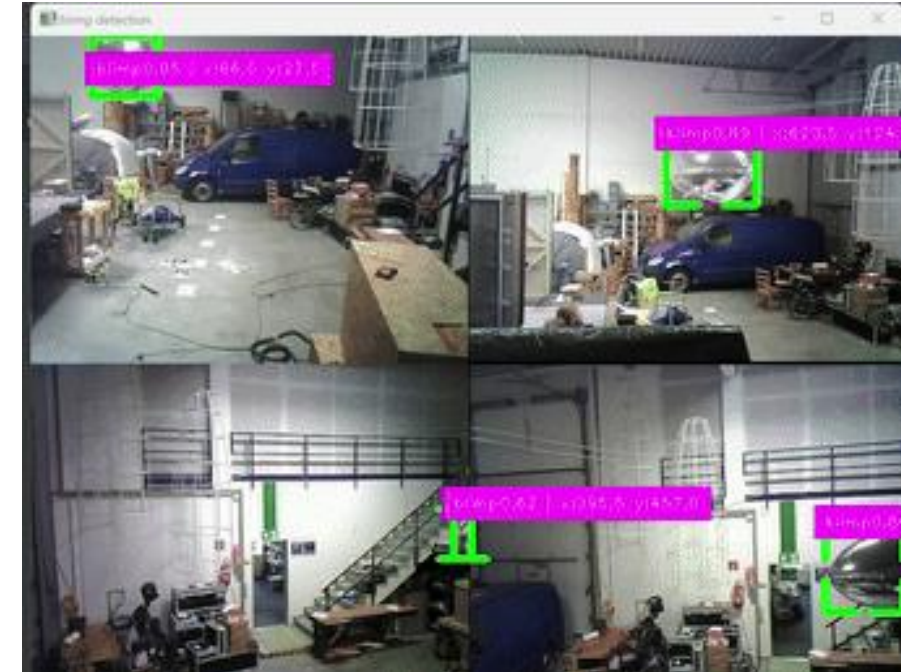


Model "20240807-py"

### Model "20240808-py"

- Dataset: around 750 specific Blimp images
- Performance: **Very Good**
- **HIGH** Precision, **HIGH** Recall, **HIGH** F1

Model can recognize the Blimp even if partially visible & different lighting



Model "20240808-py"





EP R&amp;D



Blimp Localization System



DATASETS

Label &amp; Source

Label Studio 

Labelimg



TRAIN

ultralytics  
YOLOv8

PyCharm



DEPLOY



OpenCV



PyCharm

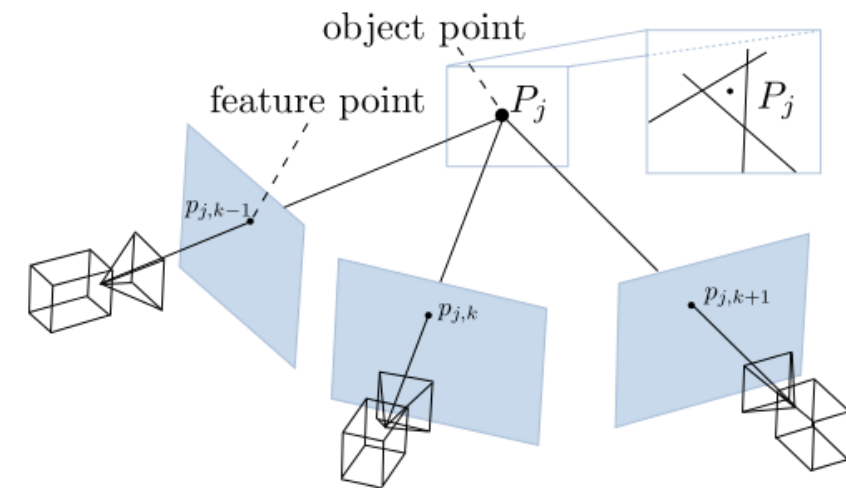
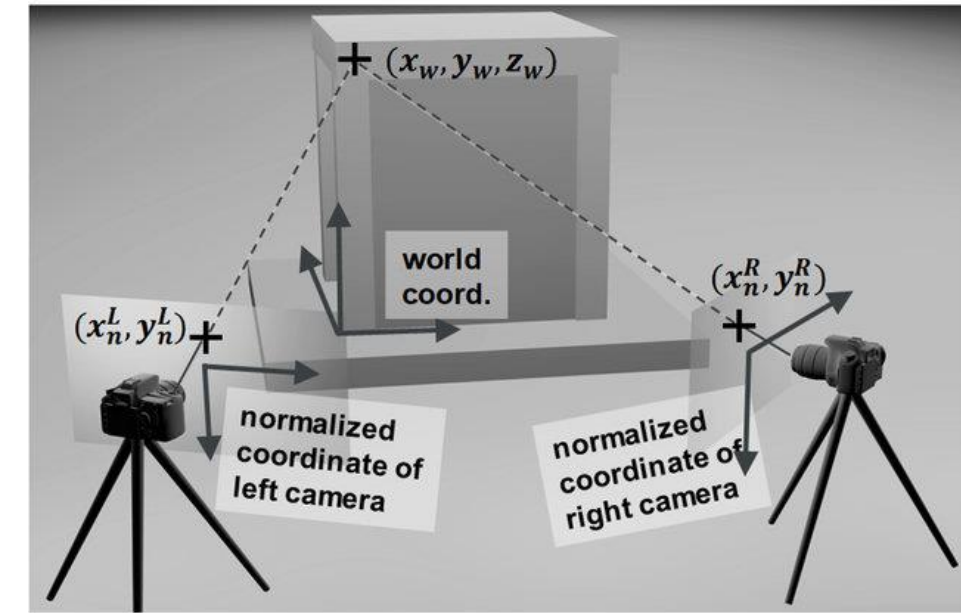


## Blimp Localization System

- Transform multiple 2D image coordinates into real world coordinates [1]
- Use a Triangulation Algorithm to localize the Blimp

### Triangulation Algorithm:

1. Input **camera parameters** (e.g., camera field of view, position, orientation, etc.)
2. Input **2D coordinates** (x-y position of the center of the bounding box around the detected Blimp) coming from the detection model from **2 cameras at least**
3. Find 3D triangulation point using **OpenCV [2]**:
  - If projections **intercept**, the intercept is identified as the **3D Blimp position**
  - Projections **may not intercept** due to **noise**, then the 3D Blimp position is identified as the **centroid** of the figure generated by the projection lines



[1] Photo: Measurement of Dynamic Responses from Large Structural Tests by Analyzing Non-Synchronized Videos. (2019). ResearchGate. <https://doi.org/10.3390/s19163520>

[2] OpenCV triangulation: OpenCV: Triangulation. (2024). Opencv.org. [https://docs.opencv.org/4.x/do/dbd/group\\_\\_triangulation.html](https://docs.opencv.org/4.x/do/dbd/group__triangulation.html)



### Future Developments:

- Improve the detection model by putting the Blimp in the real environment with different lighting conditions
- Improve the detection model with real-time localization
- Test the accuracy of the detection model and localization system in simulation
- Real environment testing and camera calibrations to refine and increase the accuracy of the localization system

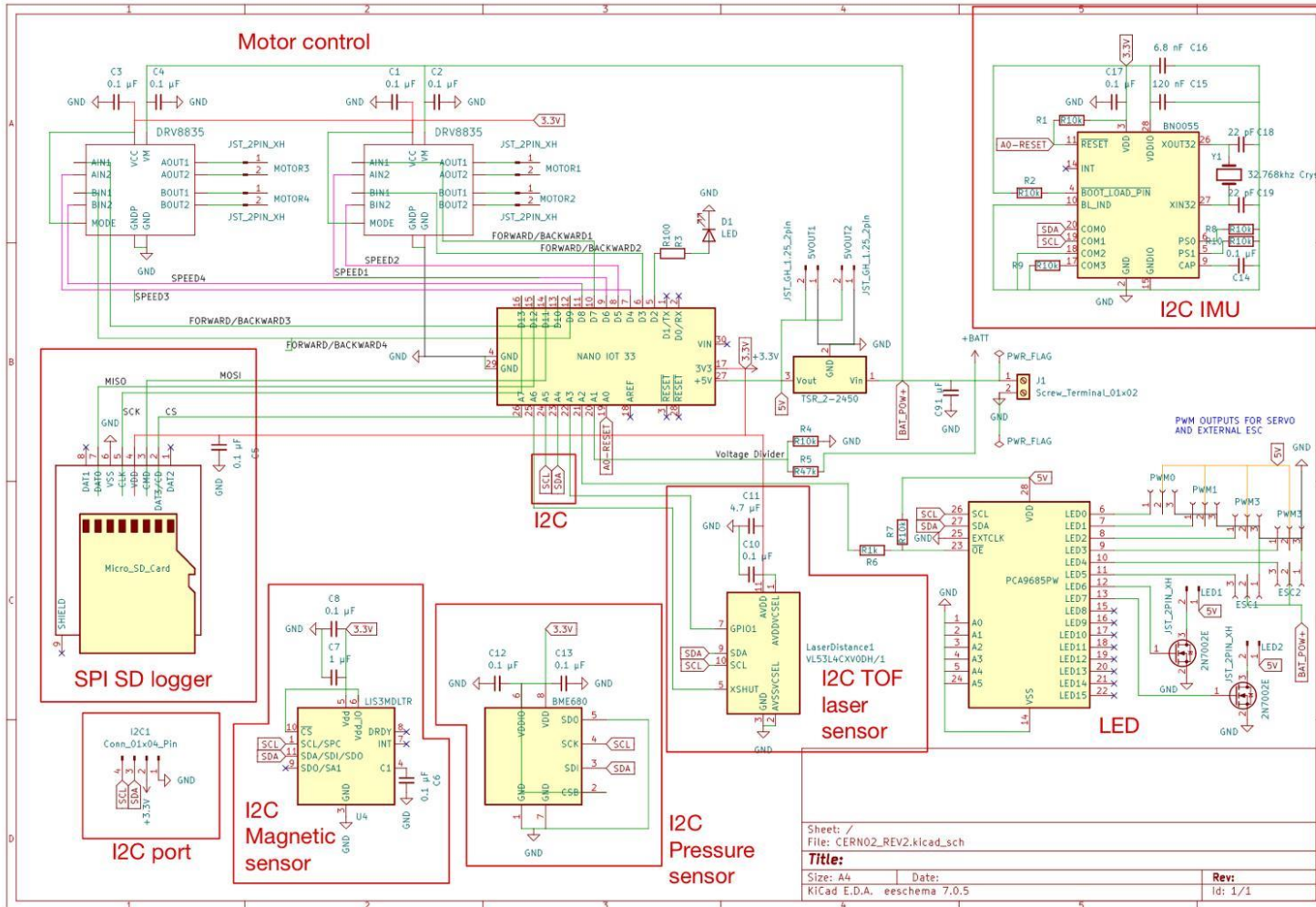




# BLIMP PAYLOAD RADIATION SENSOR

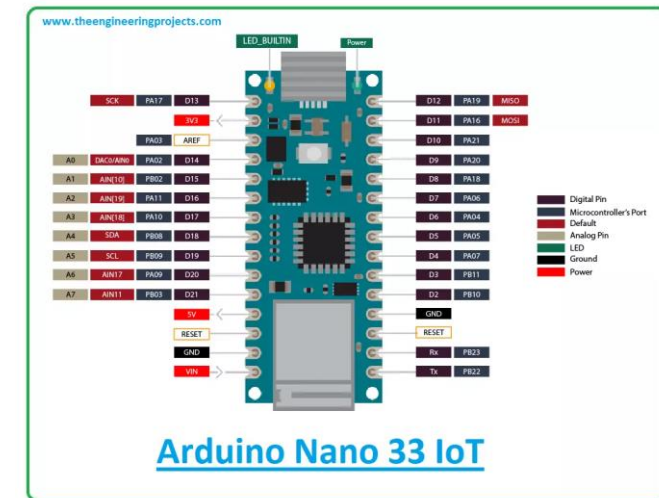


**Blimp objective:**  
Monitor radiation and magnetic fields



**Original Blimp communications**

- Most sensors on the Blimp uses **I2C** protocol
- SD logger uses **SPI** protocol
- Need to add **radiation sensor**
- **No free pins available**





## Objective:

### Radiation Monitoring:

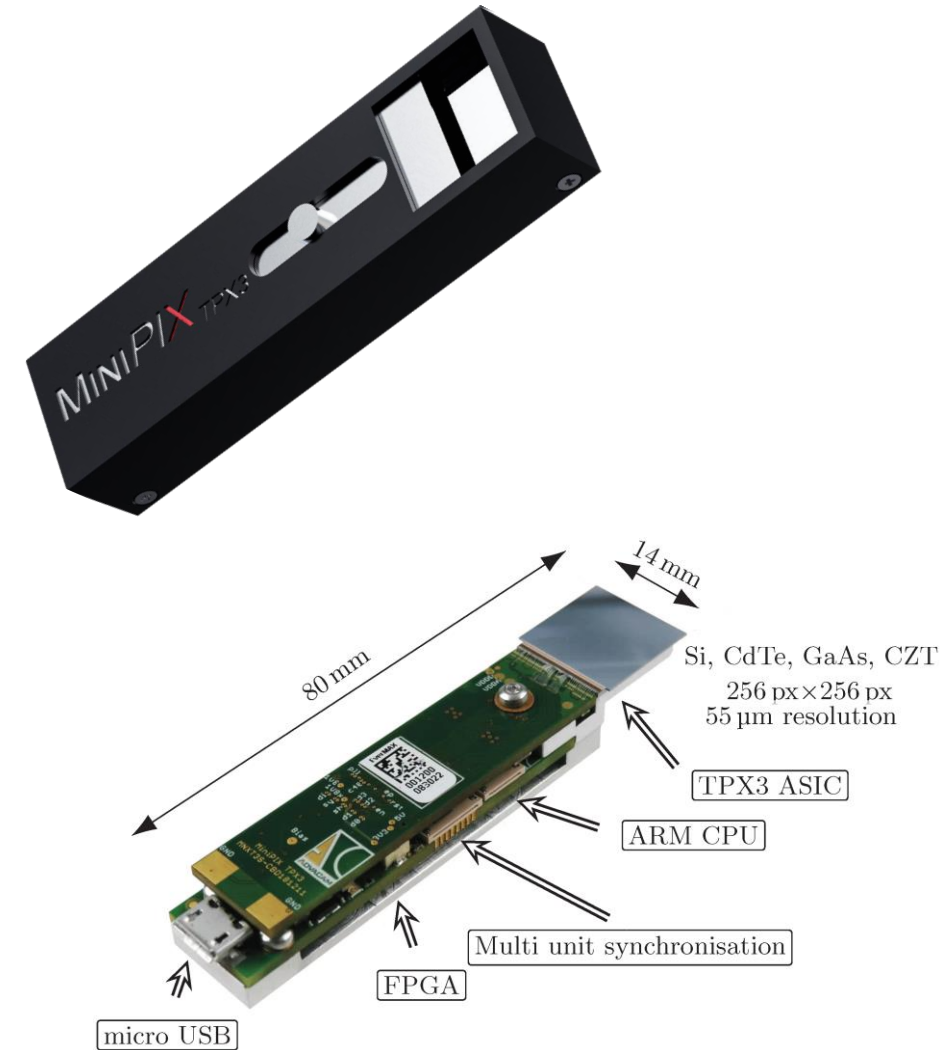
- Indicate which regions have **high radiation concentrations** that could **endanger individuals**

### Blimp protection:

- Reduce **radiation exposure and sensors damage** by **avoiding high radiation areas**

## MiniPix TPX3 Detector

- Weight: 41g
- Manufacturer: ADVACAM
- Chip: Timepix 3
- Sensor material: Silicon (Si)
- Sensor thickness: 500  $\mu\text{m}$
- Connectivity: micro-USB 2.0
- Operating mode: Time-of-Arrival(ToA), Time-over-Threshold (ToT)







### Onboard communication with a Raspberry Pi:

- Weight: 46g
- Able to install the PixetPro ARM64 API package
- Able to secure shell (ssh) to communicate with ground control station
- Able to acquire frame measurement with a Python script
- Able to read out data-driven measurements with a Python script

Raspberry Pi model 4B  
Architecture: ARM64 (64bit)  
OS: Ubuntu Desktop 23.10

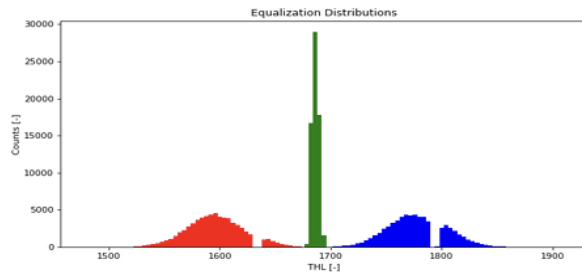
Index	Matrix	Index	ToA	ToT	FToA	Overflow
0	8704	8515971	23	8	0	
1	9222	8515971	39	16	0	
2	9742	8515972	33	15	0	
3	8962	8515971	37	17	0	
4	9226	8515972	34	18	0	
5	9744	8515972	35	11	0	
6	9485	8515972	42	24	0	
7	8965	8515971	50	21	0	
8	8966	8515972	31	26	0	
9	9225	8515971	60	15	0	
10	8449	8515970	45	10	0	
11	8963	8515971	37	23	0	
12	9743	8515972	44	16	0	
13	9482	8515972	38	24	0	
14	9484	8515972	50	25	0	
15	8964	8515971	61	21	0	
16	9223	8515971	50	16	0	
17	9224	8515971	71	21	0	
18	8705	8515970	52	13	0	
19	8706	8515970	58	15	0	
20	9483	8515971	43	11	0	
21	9486	8515972	35	13	0	
22	8192	8515970	48	1	0	
23	8448	8515970	136	13	0	
24	5272	47454362		3	9	0
25	20174	56169263		2	14	0
26	20672	65701144		2	9	0
27	1250	88720733		69	18	0
28	994	88720733		54	17	0
29	38404	162659485		5	25	0

Data-driven measurements

## Procedures of getting the Radiation dose :

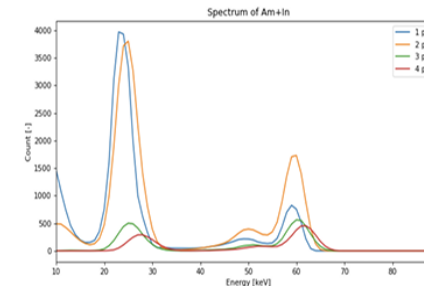
### 1. Calibrate Sensor

ensuring each pixel of the detector will have the **same ToT with the same type of particles**  
**Threshold Equalization**



Parameter	Value
Mean THL	1686.206
Std. Dev	7.422
Masked Pixels	26
Final THL	1628

### Energy Calibration in ToT Mode



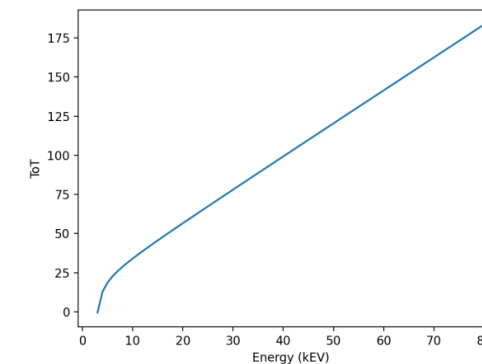
Source	Energy	1	2	3	4
Fe	5.725	5.124	8.106		
In	24.047	23.628	24.696	25.356	27.419
Am	59.499	59.378	59.748	60.546	61.734

Coefficient	Mean value
A	2.100
B	15.903
C	23.483
T	1.967

### 2. Energy Calibration

use **known sources** (Fe, In and Am) to construct the **"Energy to ToT graph"**

3. Analyze "Energy to ToT graph"  
 match **energy of each incoming particle** with ToT operating mode



5. Calculate **effective dose** from total energy

4. Add up the **total energy** over a certain period



## Future Developments:

- Use the Raspberry Pi Zero instead of the Raspberry Pi 4B to reduce the load on the Blimp (maximum payload of around 200g)  
46g -> 16g
- Blimp onboard ssh communication testing
- Radiation Dose Calibration of the sensor in real environment





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## Overall Conclusion:

### Blimp Localization System:

- Latest detection model **efficiently identifies the Blimps** in video frames
- The first developed detection models gave **False Positives**
- **Significant improvements** were obtained after refining the detection model
- The localization system must use **triangulation with multiple camera views**

### Onboard radiation monitoring with MiniPIX TPX3 detector:

- A **Raspberry Pi** was used for data readout, due to **communication and weight limits**
- Implement the procedure to get the **dose rate from energy** using ToT measurements
- Refinements and real-environment testing are required







**THANK YOU FOR YOUR ATTENTION**

BACKUP SLIDES





## You Only Look Once (YOLO):

- YOLO frames object detection as a **regression problem**, predicting bounding boxes and associated **class probabilities** directly from **full images in a single evaluation**
- To predict each bounding box, or object on the image, the YOLO algorithm **adopts characteristics from the entire image**.
- Additionally, it simultaneously predicts **all bounding boxes for a picture** in all of the classes.
- The image is divided into a  **$S \times S$  grid**, and predictions are made for each grid cell regarding  $B$  bounding boxes, their corresponding confidence, and the probability of the  $C$  class. The tensor encoded with these predictions is  **$S * S * (B * 5 + C)$**

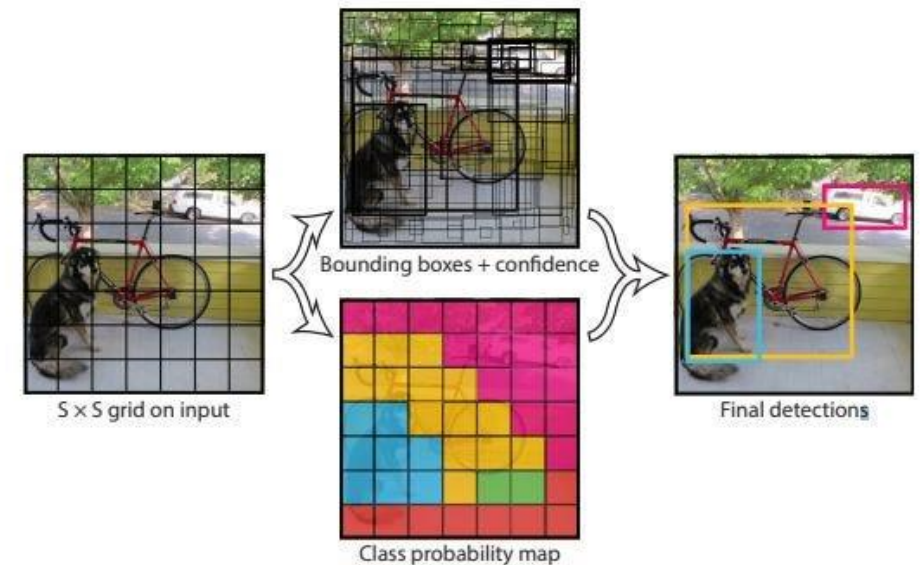


Figure 1: Working principle of YOLO





## Hybrid Silicon pixel detectors:

- Aluminum layer on top
- n-type implant just below the top surface,
- p-type implant pixels toward the bottom
- **High voltage** (positive) connection to the **aluminum surface**
- **Negative connection** to the **p-type** silicon layer
- Via a layer of **solder bumps**, a hybrid readout **ASIC** (**Application Specific Integrated Circuit**) is attached to the sensor component.

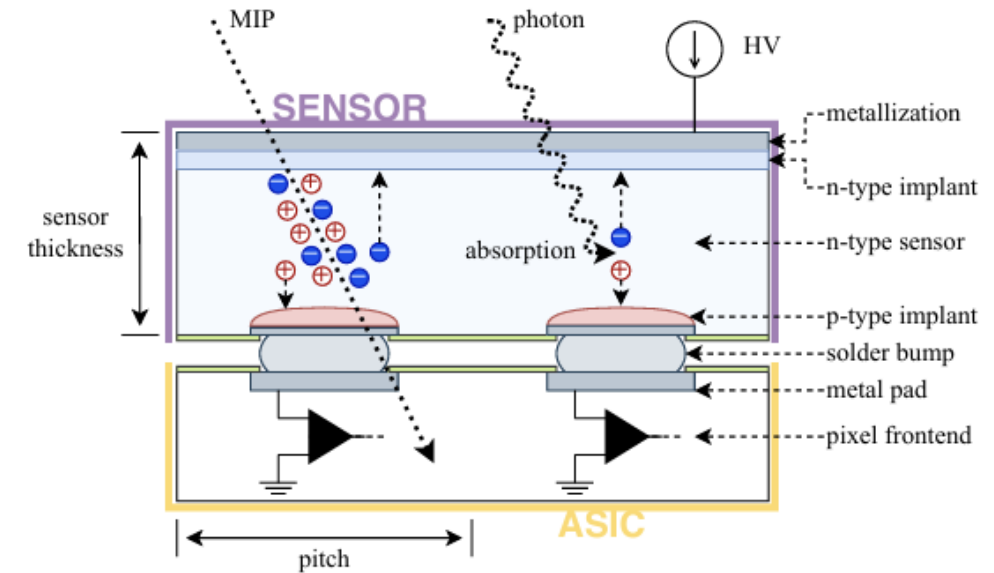
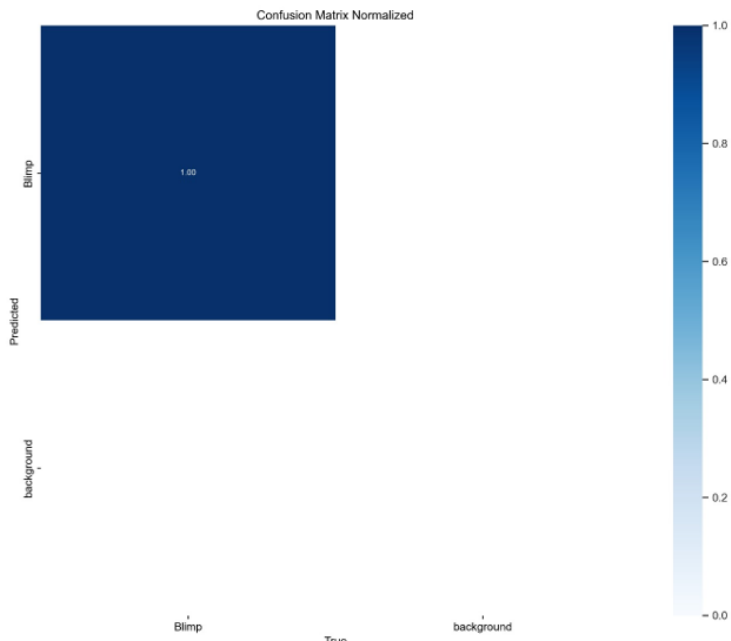


Figure 27: Schematic cross-section of a hybrid pixel detector

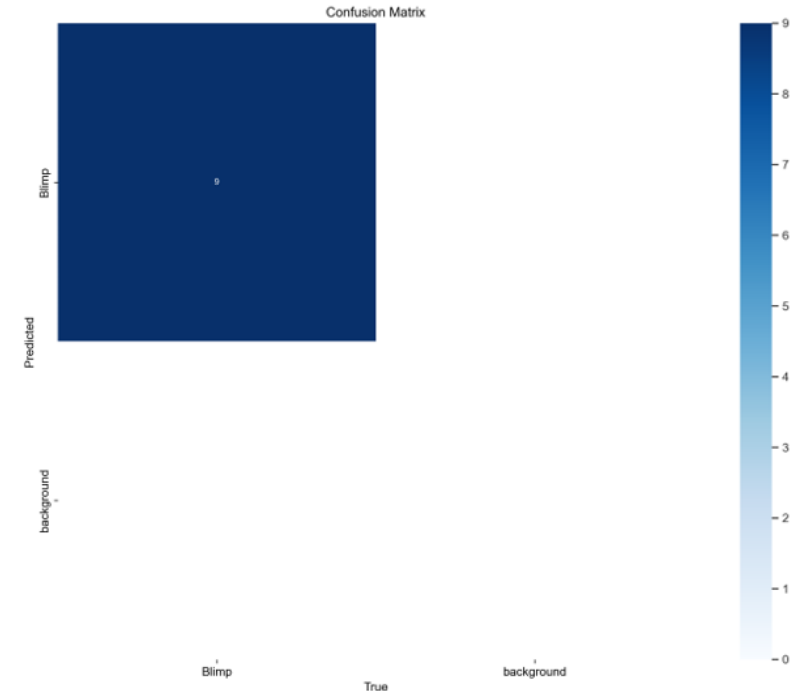
Models

Confusion Matrix

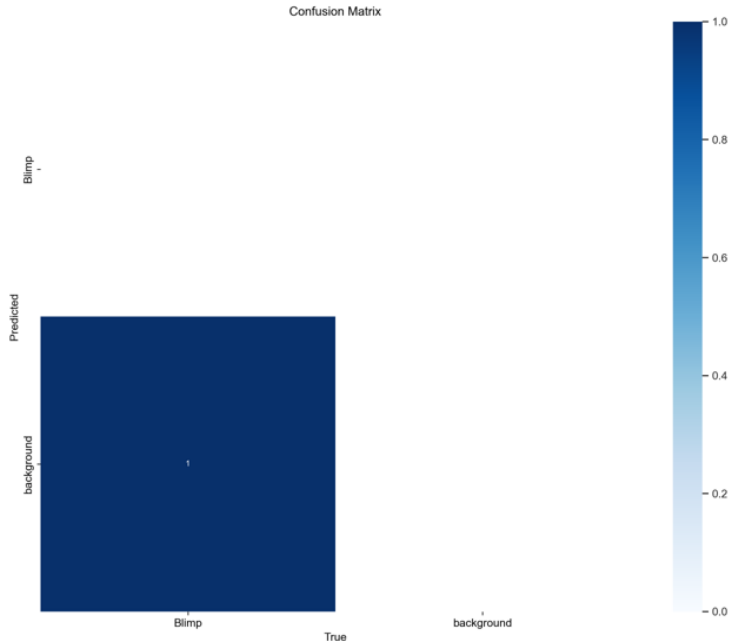
20240731-py



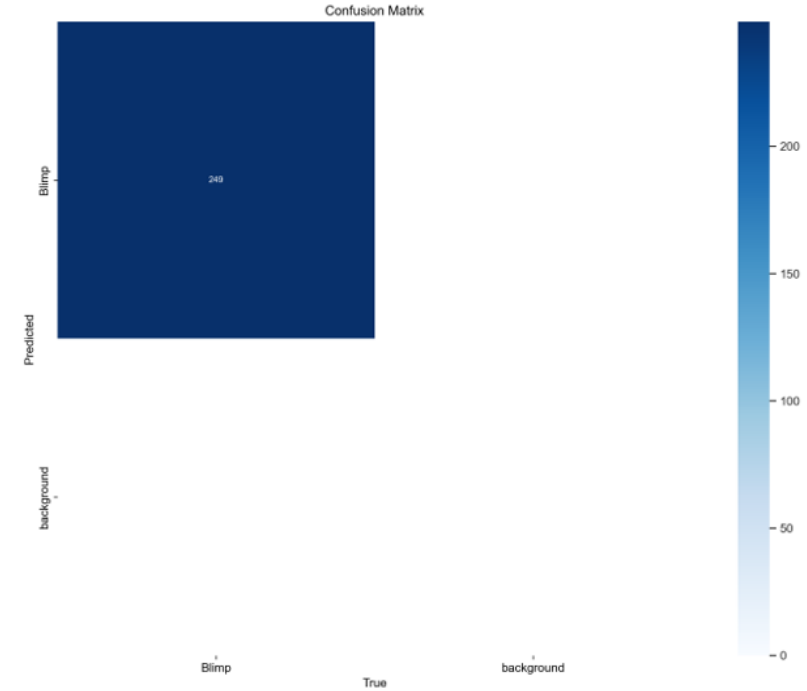
20240806-py



20240802-py

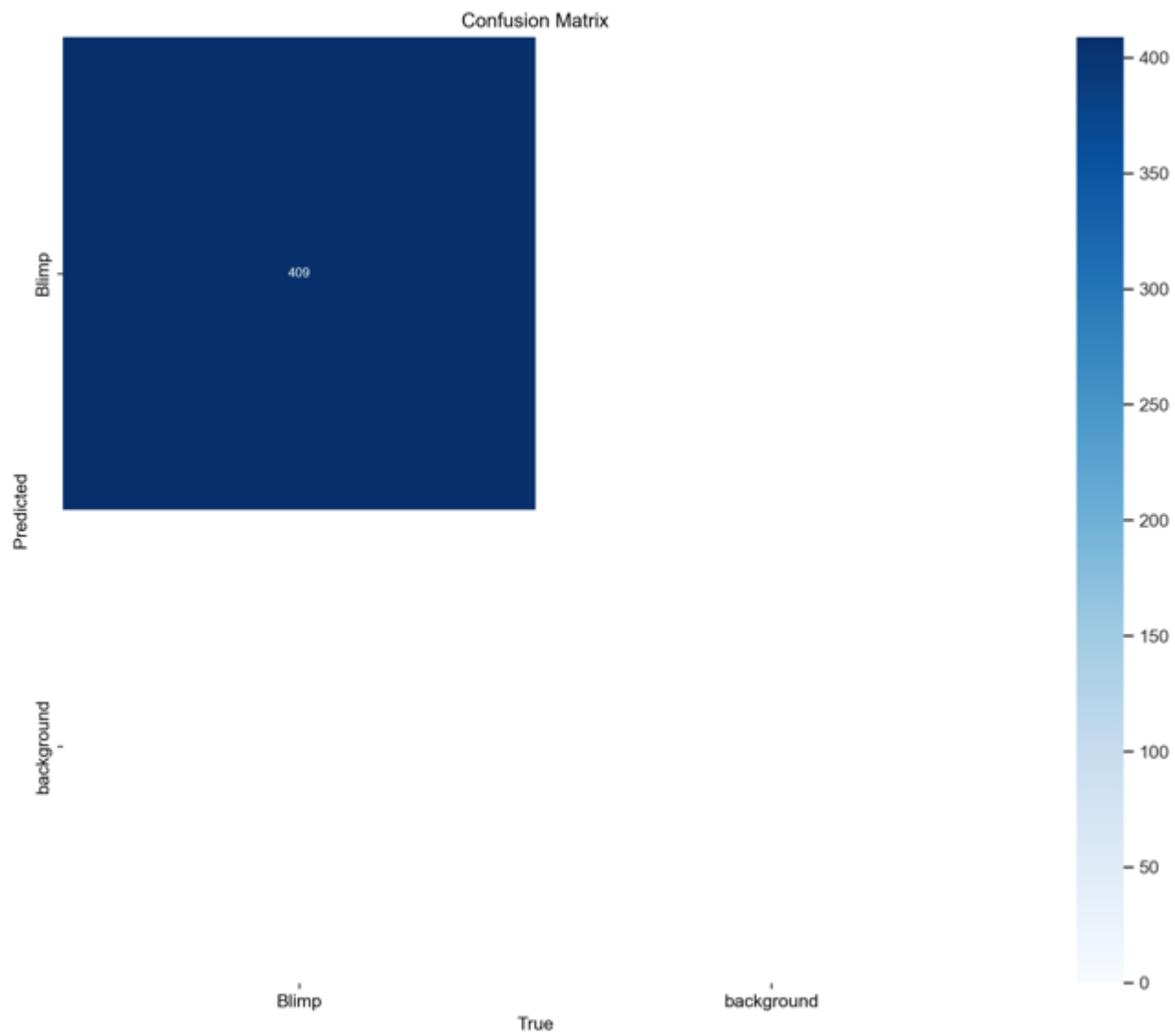


20240807-py





20240808-py







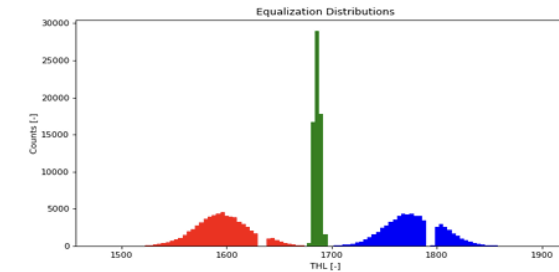
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With reference to ADVACAM Calibration documents

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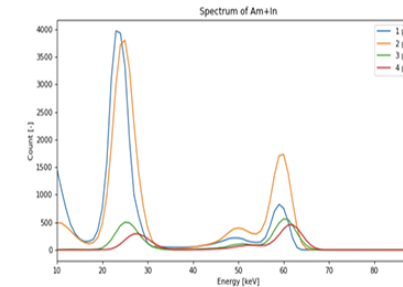


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