



# Image signal selection for trigger

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- Conclusions
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# 1. Introduction

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# Motivation

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- One major **challenge** for the **CYGNO experiment** in the long term will be to **store and analyse all the data produced by the detector**.
  - Each run containing **400 images** from Fusion (Quest) needs **~1.36 Gb (2.01 Gb)** to be stored.
  - A **single day of acquisition** may produce **~215 Gb (327 Gb)** of data.
- The motivation of this work was to study algorithms capable of **distinguishing images or regions** containing a **signal of interest** and **background events**.
- An algorithm capable of doing this task was called **image based trigger algorithm**.

# What was done

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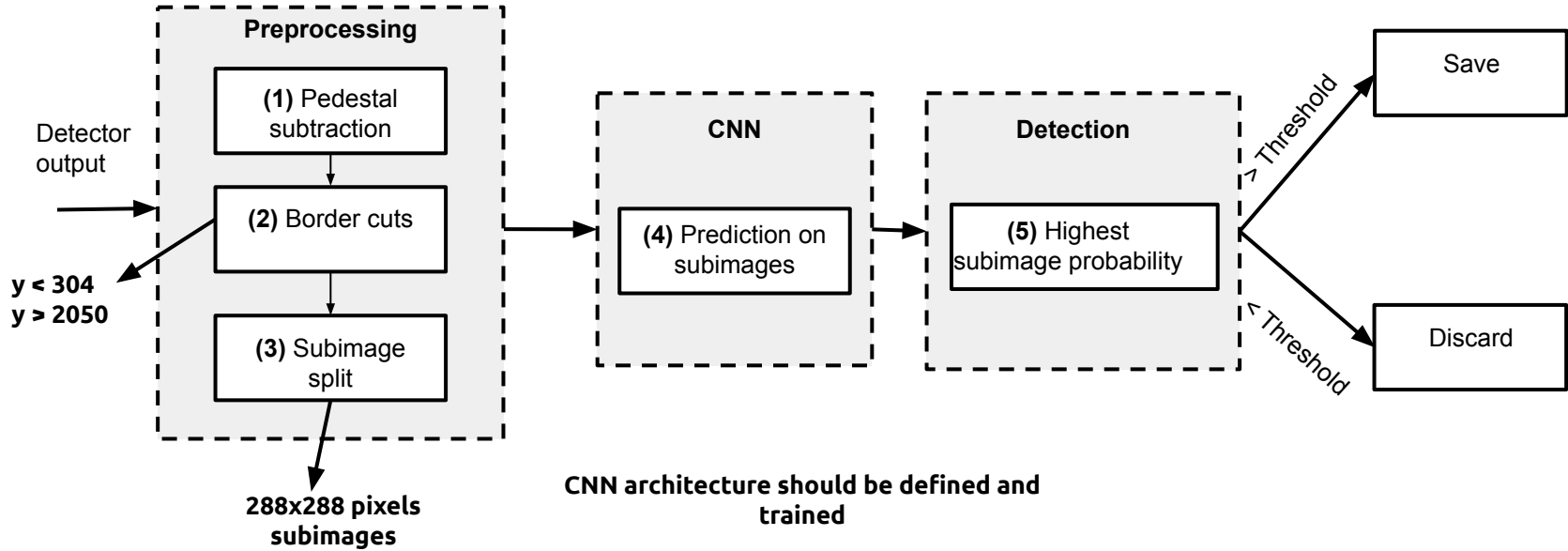
- Two approaches were proposed:
  - **Image level trigger** using **filtering** and **CNNs**.
  - **Pixel level trigger** using **filtering**.
- A performance analysis was done using simulated and real data from Fusion (focused on **low energy** events):
  - Trigger **detection performance**.
  - Reconstruction comparison.
  - **Processing time**.



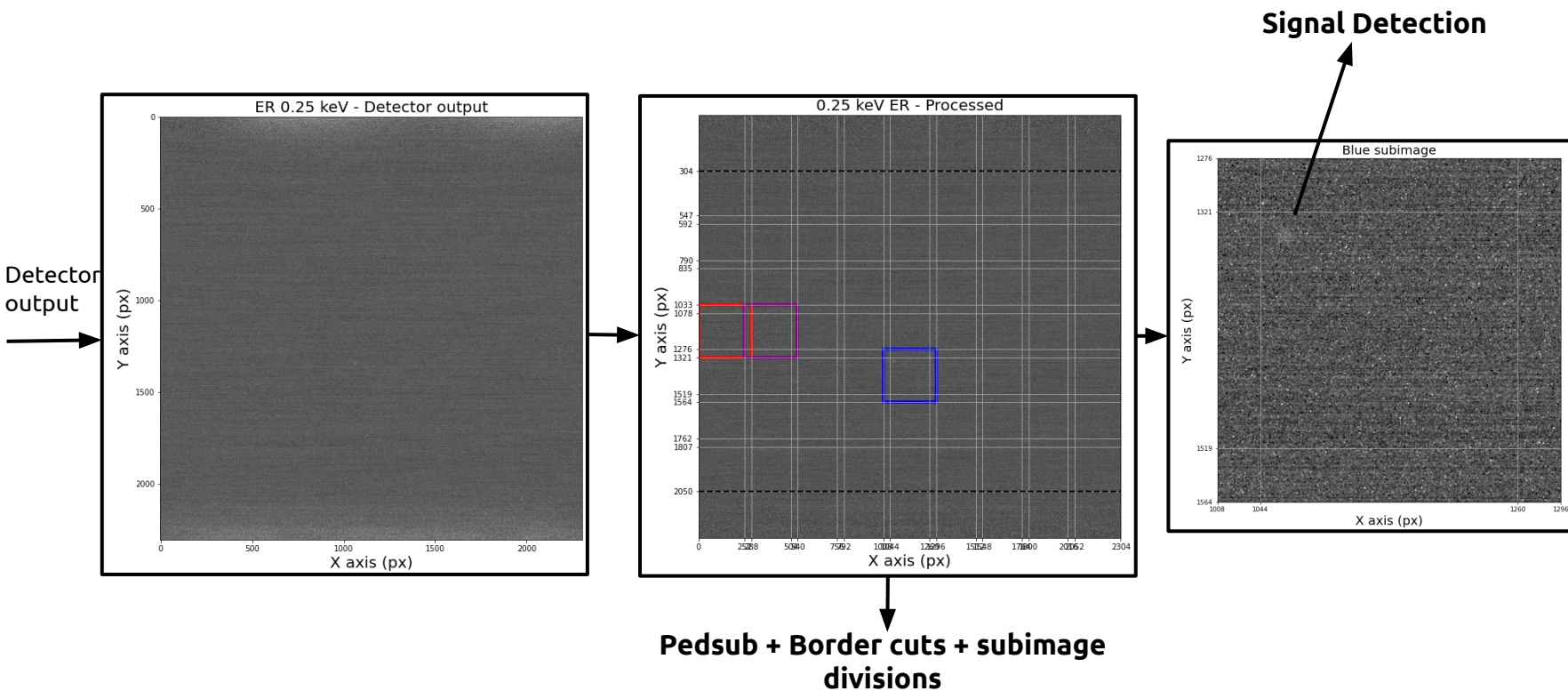
## **2. Algorithms**

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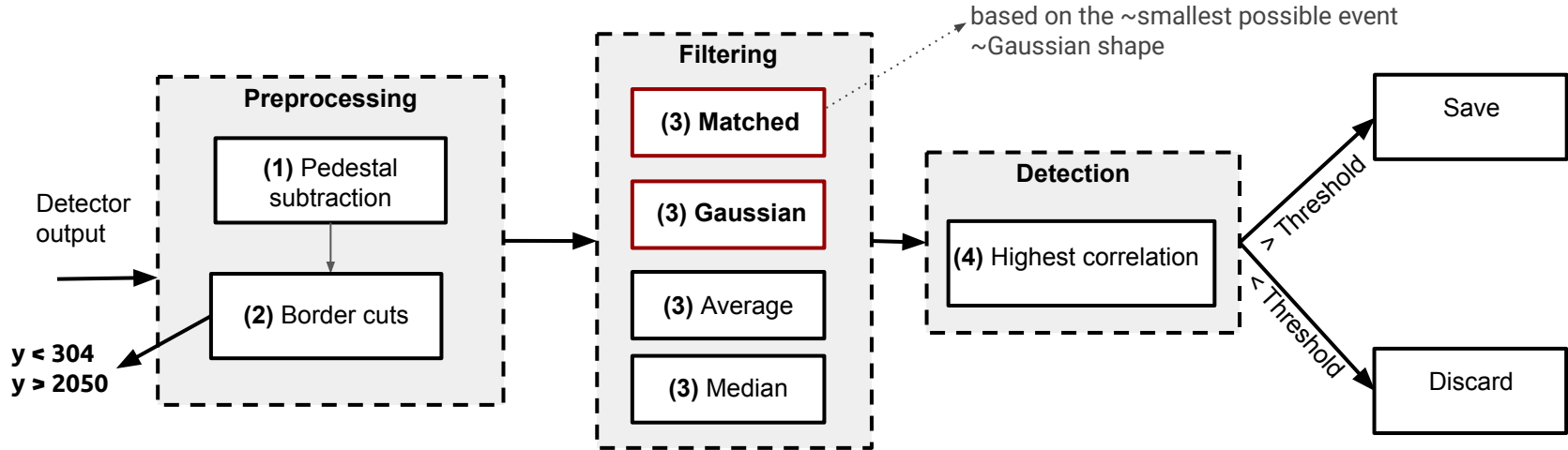
# CNN based image level trigger



# CNN based image level trigger



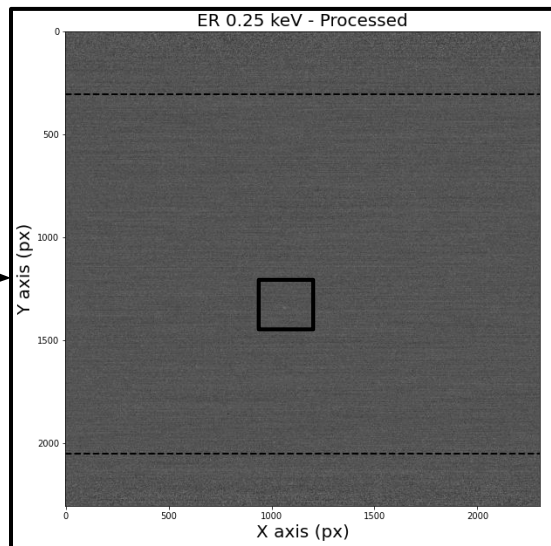
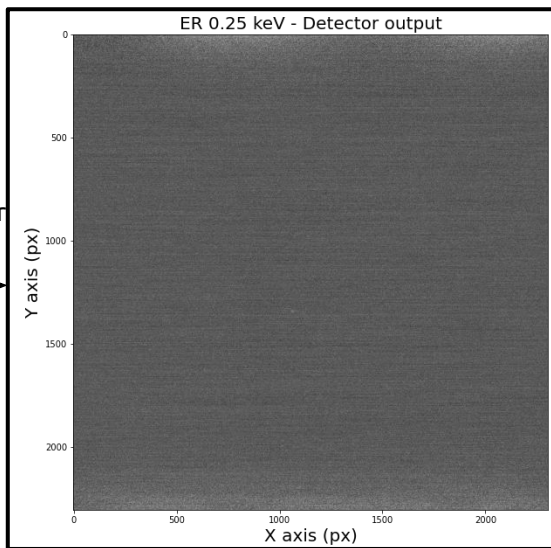
# Filtering based image level trigger



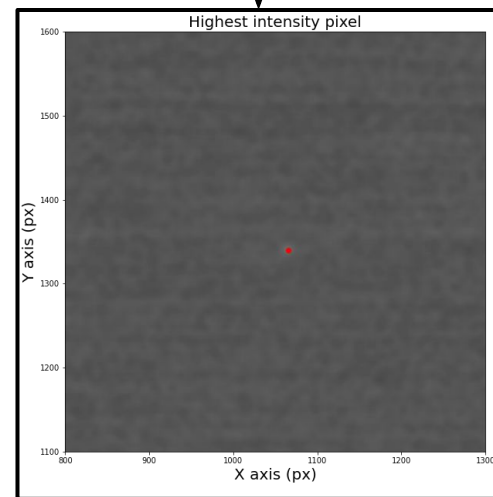
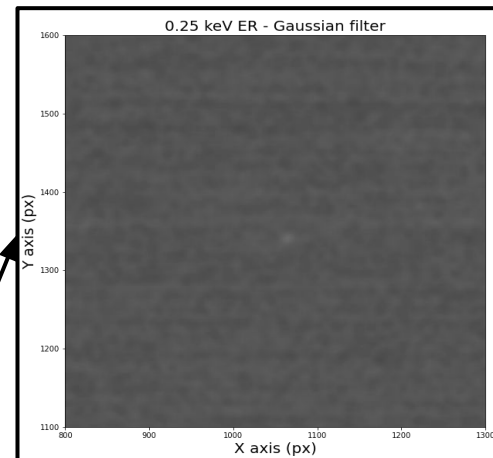
Filter parameters and detection threshold  
selected based on training data

# Filtering based image level trigger

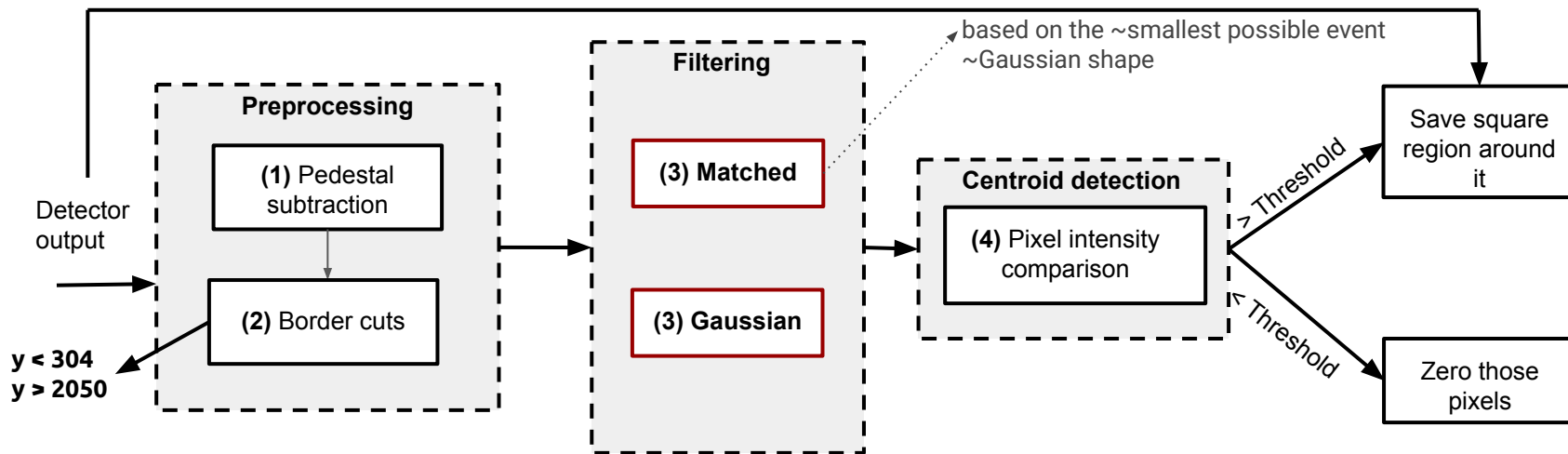
Detector output



**Pedsub + Border cuts**



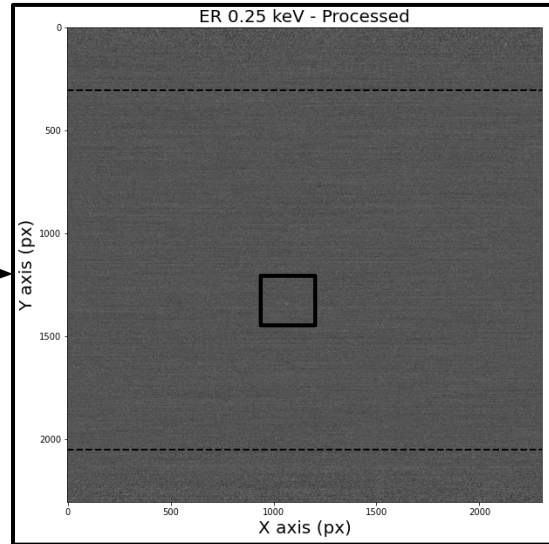
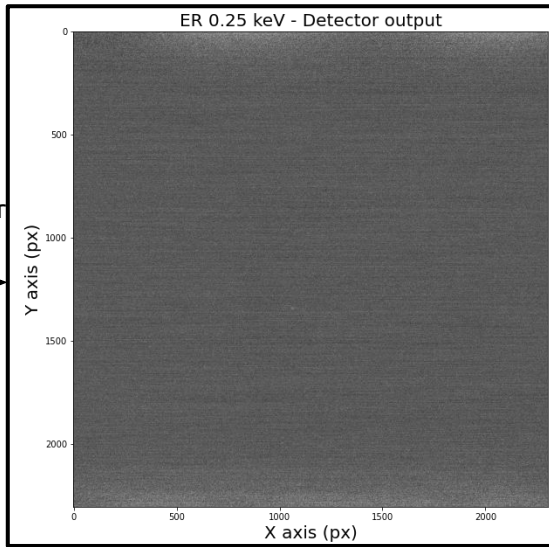
# Filtering based pixel level trigger



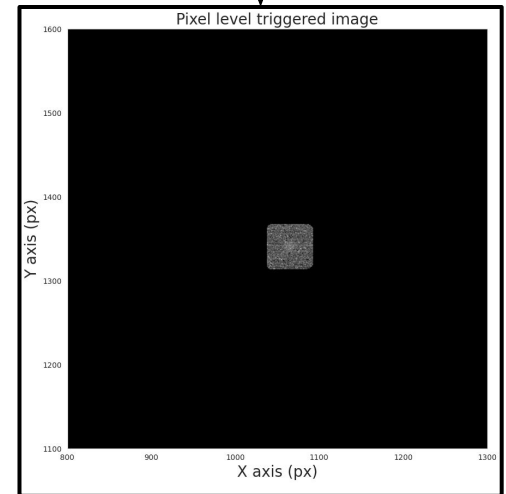
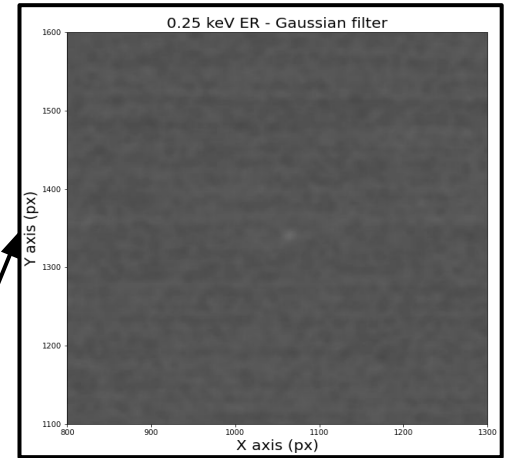
Filter parameters and detection threshold selected based on training data

# Filtering based pixel level trigger

Detector output



**Pedsub + Border cuts**

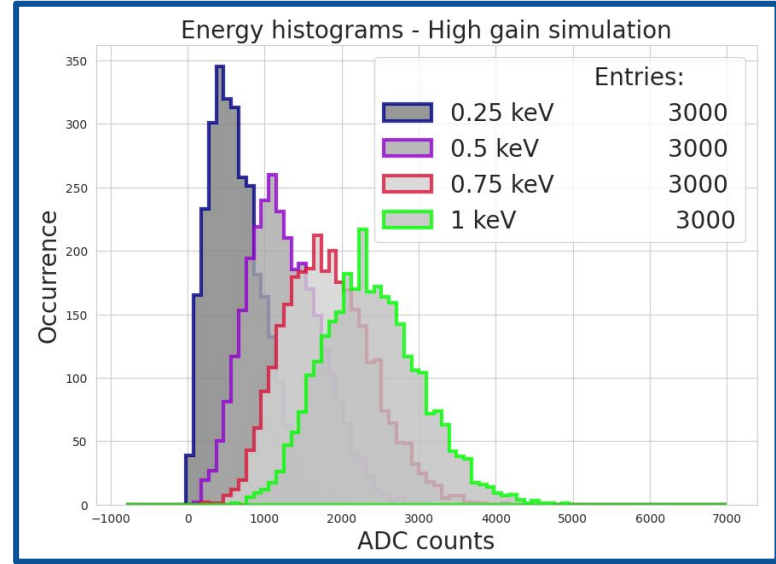
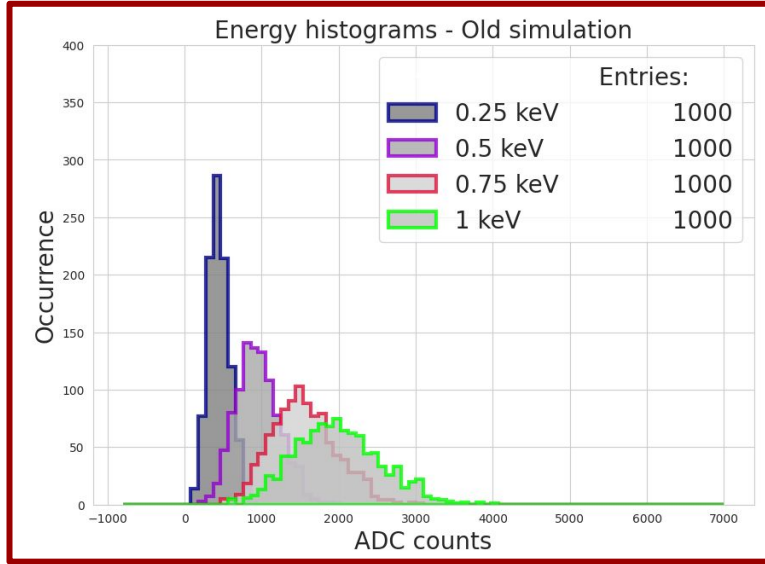




## **3. Development**

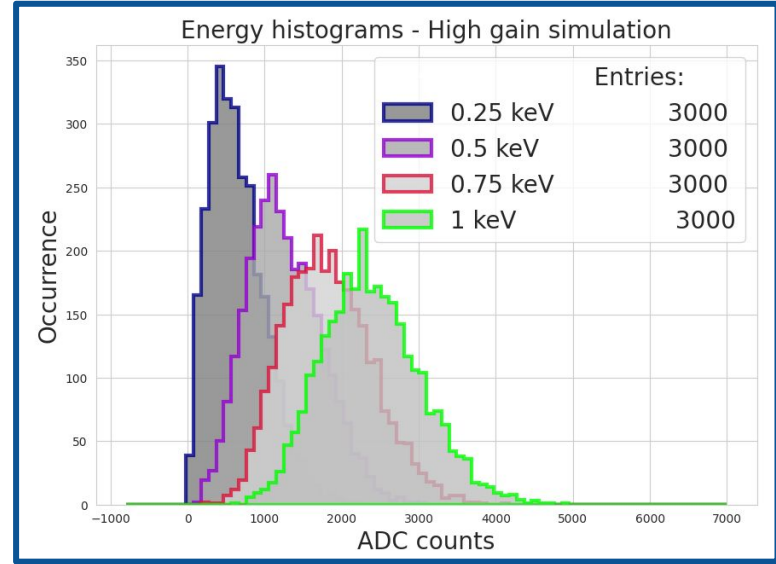
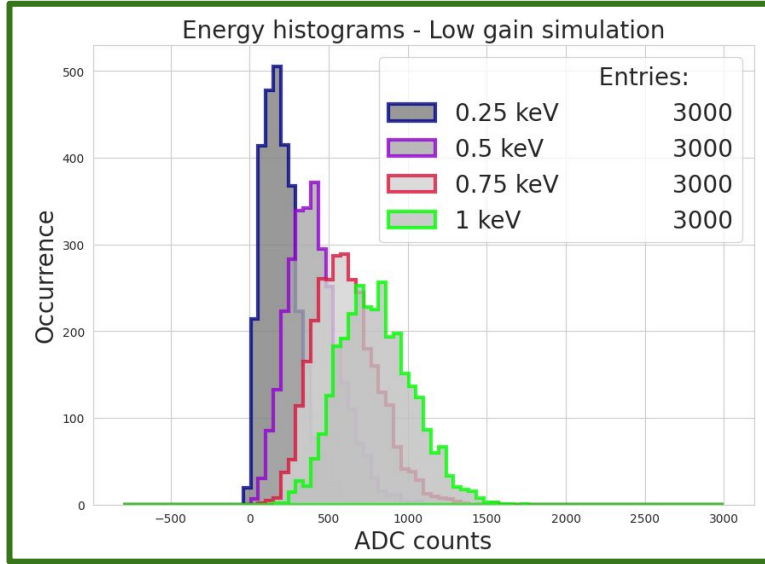
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# High gain Fusion simulation



- The new high gain simulation energy in ADC counts is slightly higher and wider.
  - **0.25 keV:**  $[446.17 \pm 138.45]$  vs  $[650.76 \pm 367.88]$
  - **0.5 keV:**  $[946.93 \pm 278.46]$  vs  $[1256.11 \pm 479.44]$
  - **0.75 keV:**  $[1546.18 \pm 418.33]$  vs  $[1824.22 \pm 570.07]$
  - **1 keV:**  $[1992.36 \pm 556.59]$  vs  $[2386.86 \pm 639.05]$

# Low gain Fusion simulation



- The **low gain** simulation energy in **ADC counts** is **~3 times smaller** than **high gain**.
  - **0.25 keV:**  $[200.89 \pm 116.91]$  vs  $[650.76 \pm 367.88]$
  - **0.5 keV:**  $[408.99 \pm 166.39]$  vs  $[1256.11 \pm 479.44]$
  - **0.75 keV:**  $[609.78 \pm 201.59]$  vs  $[1824.22 \pm 570.07]$
  - **1 keV:**  $[801.70 \pm 230.01]$  vs  $[2386.86 \pm 639.05]$
- It is **expected** to be **harder** to **detect** these **signals**.

# Models training

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- Simulation were split into **training, validation** and **testing** datasets (60%-20%-20%).
  - **Pedestal images** were selected from **Run5** to be used as **noise** and to be **combined** with the **simulation**.
- A **scan** using **different filter configurations** (kernel size, sigma, etc) was done using the **training** and **validation datasets**.
  - Each **configuration** generates **two distributions: highest correlation** on **signal** and **noise**.
  - The **configuration** with the **highest AUC** from the **ROC curves** is selected (**better discrimination** between **distributions**).
- Several **CNN architectures** were **trained** using the **training** and **validation datasets**.
  - After each **epoch** the **CNN updates** the **weights** of its architecture to **minimize** the **loss** between its **prediction** and **true labels**.

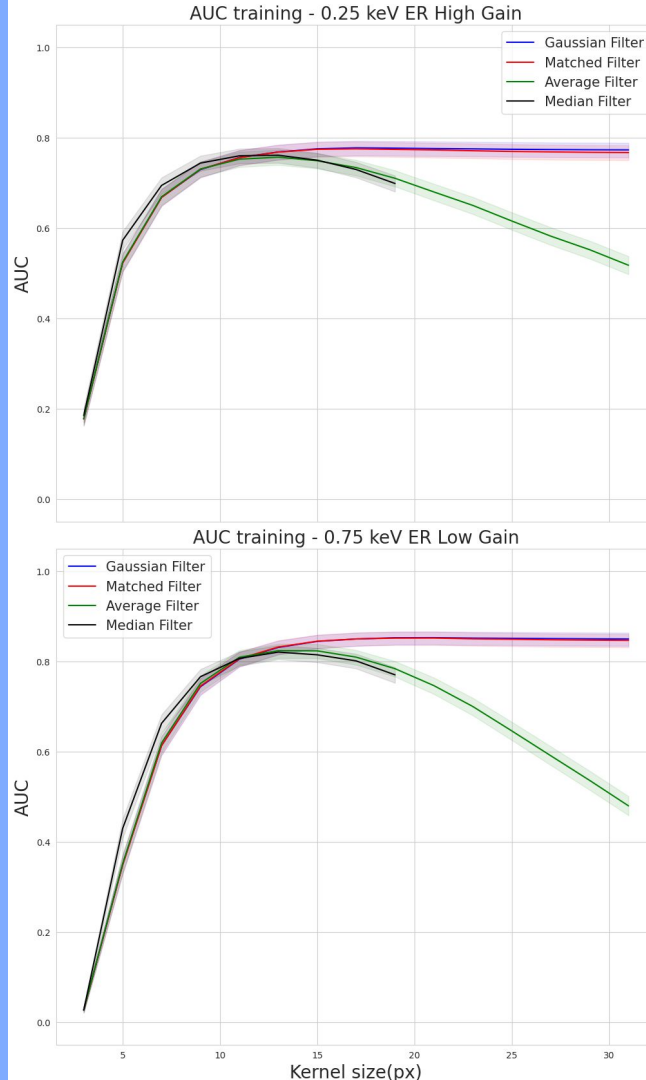
A large blue geometric shape, resembling a parallelogram or a trapezoid, is positioned on the left side of the slide. It has a diagonal edge on the right side, separating it from the white background.

## 4. Results

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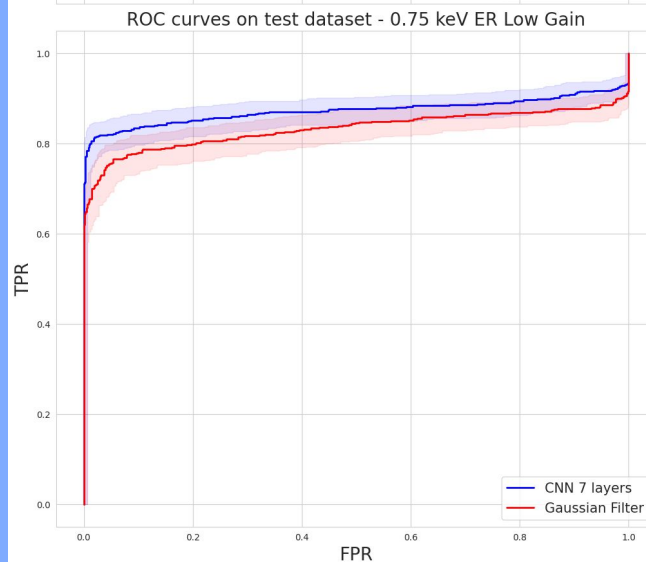
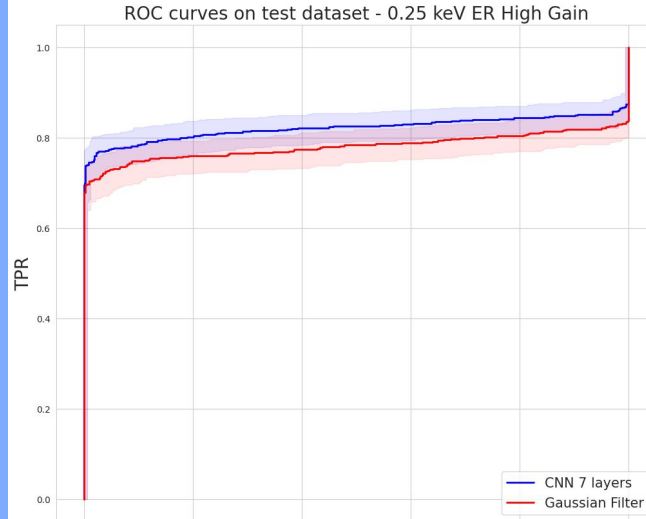
# Image level trigger

- The **same training procedure** for the **filtering** methods was used with the **new data**.
  - **Gaussian** and **matched filter** still provide the **best results**.
  - **Kernel sizes** of **17 (HG)** and **21 (LG)** were selected.
  
- The **CNN models trained** with the **old simulation** were used as a **start point**.
  - **New training** will be done for the **Quest** in the **future**.



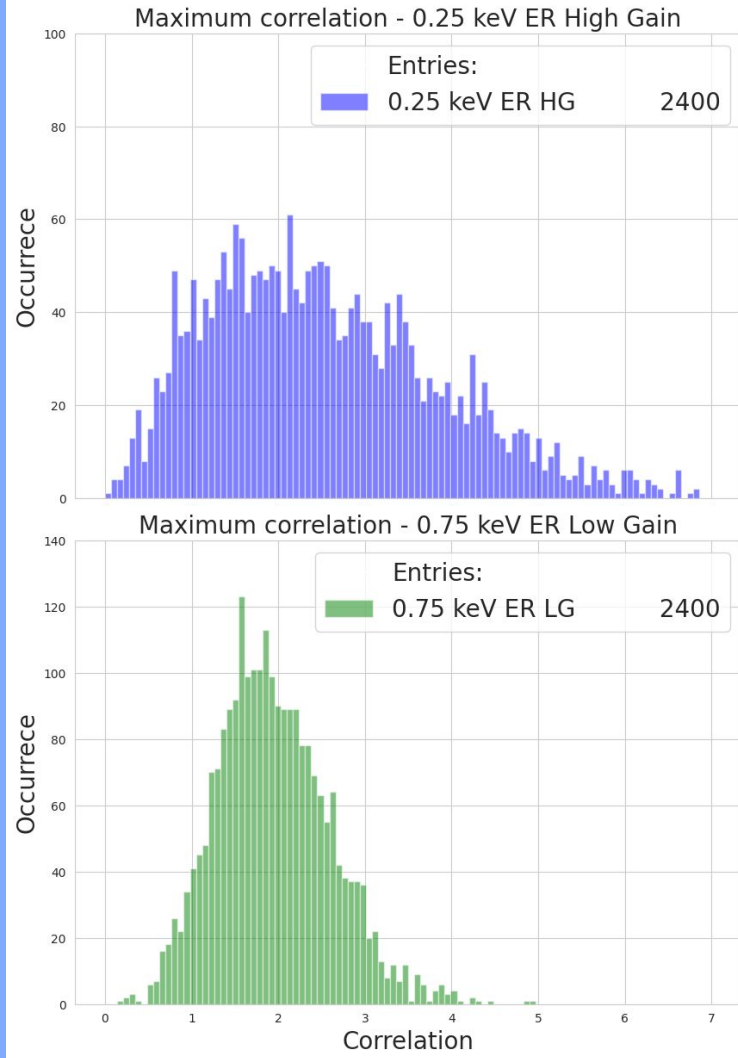
# Image level trigger

- The **new high gain simulation** showed **slightly worse results** compared to the **old** one.
  - It has more **low ADC counts events** due to its higher **std**.
  - **Gaussian Filter:** ~75% signal detection with 10 % false alarm.
  - **CNN:** ~74% signal detection with 0.5% false alarm.
- The **low gain 0.75 keV ER** shows **similar** results compared to the **0.25 keV ER** from the old simulation.
  - **Gaussian Filter:** ~78% signal detection with 10% false alarm.
  - **CNN:** ~78% signal detection with 0.5% false alarm.



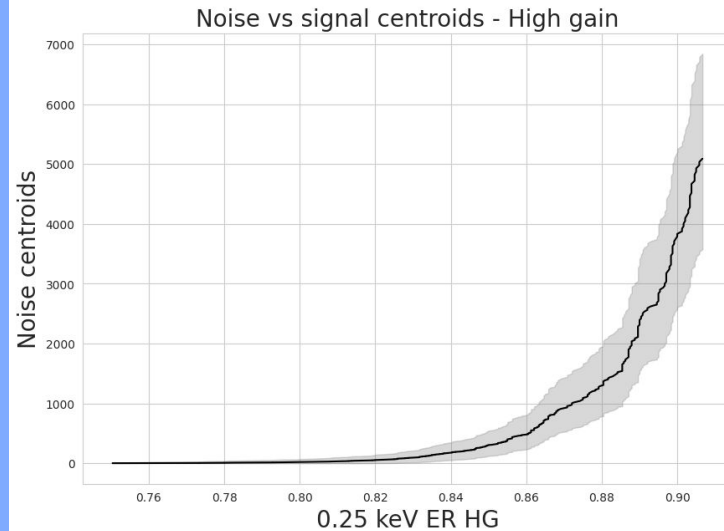
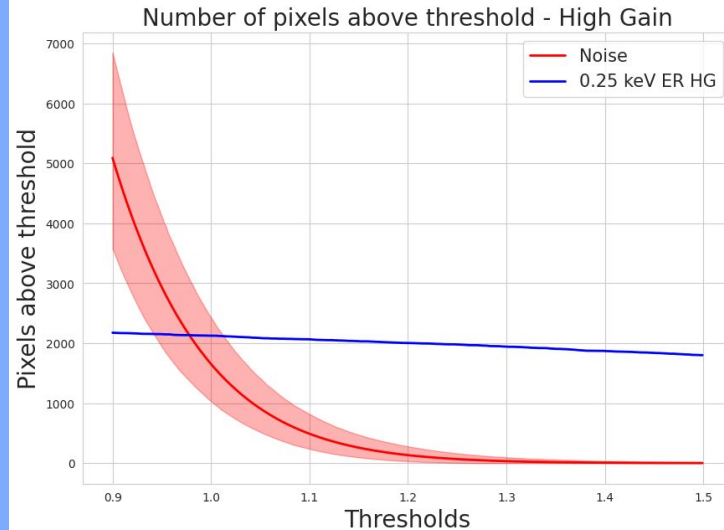
# Pixel level trigger

- The **pixel level trigger** needs **two parameters: threshold** (centroid detection) and **radius** (save region).
  - The **threshold** should **detect** as much as possible of the **signal** while **discarding noise**.
- **Possible ranges of thresholds** were selected to see the number of **noise centroids** detected on **noise dataset**.
  - **High gain:** [0.9, 1.5]
  - **Low gain:** [0.8, 1.2]



# Pixel level trigger

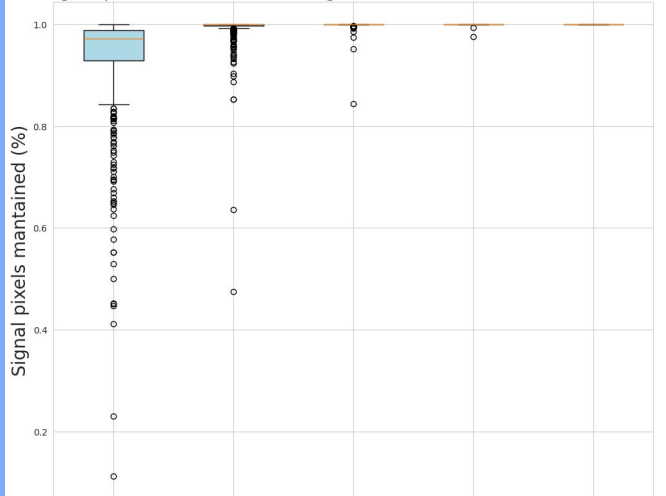
- The **number of noise centroids** detected **start high** and **rapidly decreases** as the **threshold increases**.
  - **5000 centroids** could **retain 2 million pixels** in the image with a **radius of 20** for example.
- The **lower plot** gives a better look at the possible **ideal threshold**: the **knee**.
  - **High gain threshold: 1.123**
  - **Low gain threshold: 0.988**



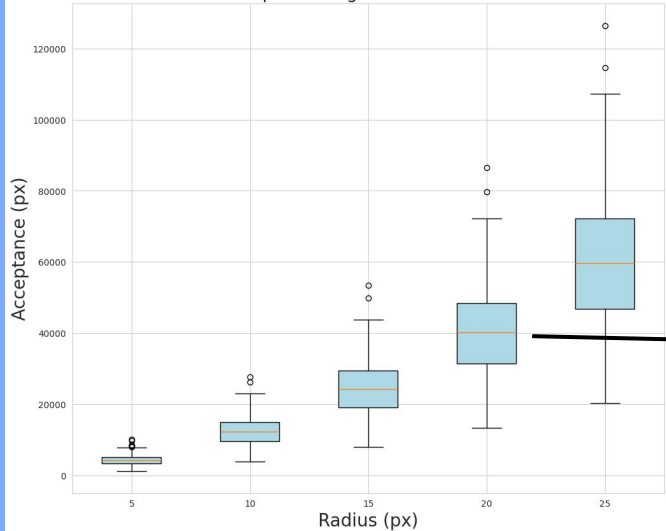
# Pixel level trigger HG

- The algorithm was applied on the **HG** data to select the **radius**.
  - A **radius of 20** is **enough to detect almost all** the **pixels** of the **signal detected**.
  - **~86%** of the **0.25 keV ER HG** were **detected**.
- The test dataset was saved after the algorithm was applied.
  - Original full images: 7.1 GB
  - Images as root histograms: 229 MB
  - Images as sparse arrays (scipy): 185.7 MB
  - Images as sparse arrays (root): 188.5 MB

Signal pixels maintained on images based on radius - ER 0.25 keV HG



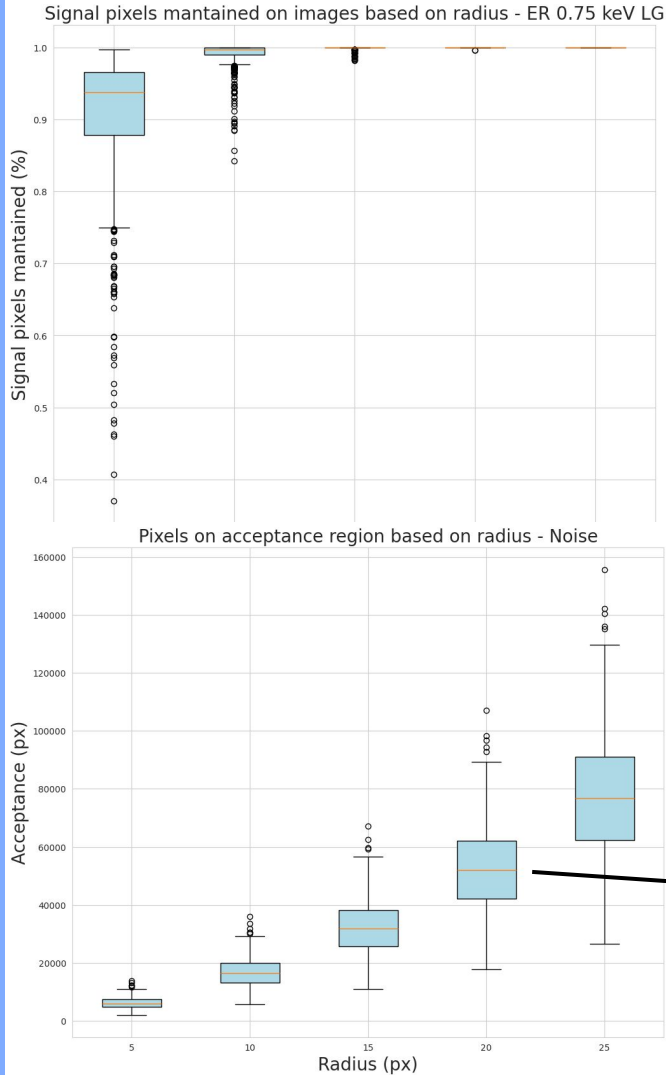
Pixels on acceptance region based on radius - Noise



~0.7% of image pixels

# Pixel level trigger LG

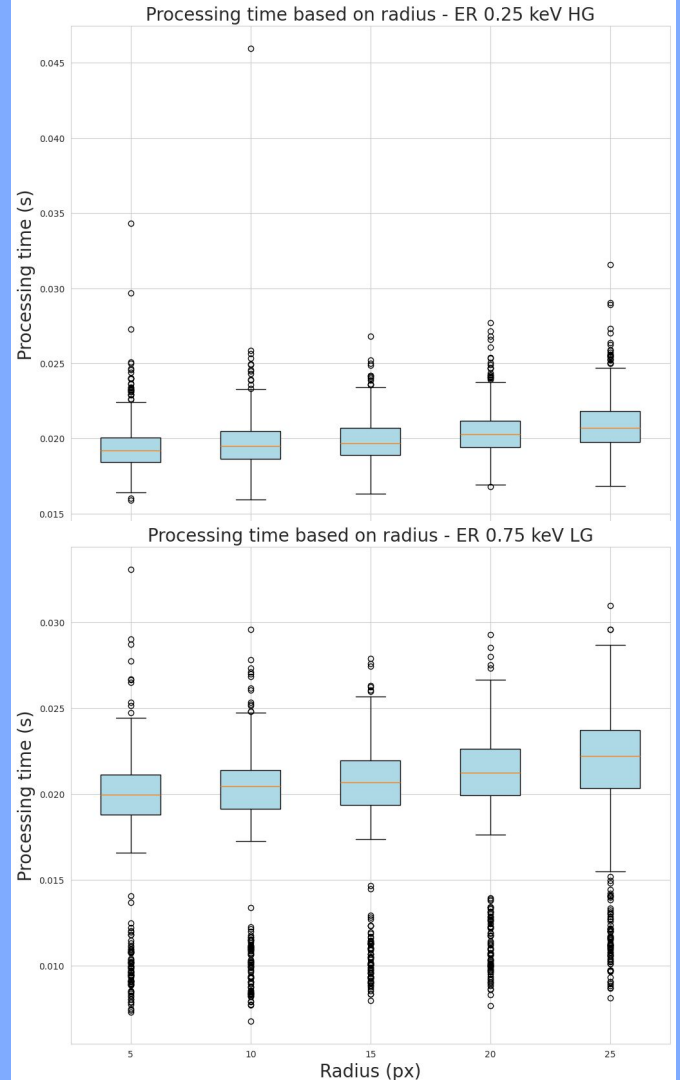
- The algorithm was applied on the **LG** data to select the **radius**.
  - A **radius of 20** is **enough to detect almost all** the **pixels** of the **signal detected**.
  - **~93%** of the **0.75 keV ER LG** were **detected**.
- The test dataset was saved after the algorithm was applied.
  - Original full images: 7.1 GB
  - Images as root histograms: 284 MB
  - Images as sparse arrays (scipy): 237.6 MB
  - Images as sparse arrays (root): 241.3 MB



# Processing time

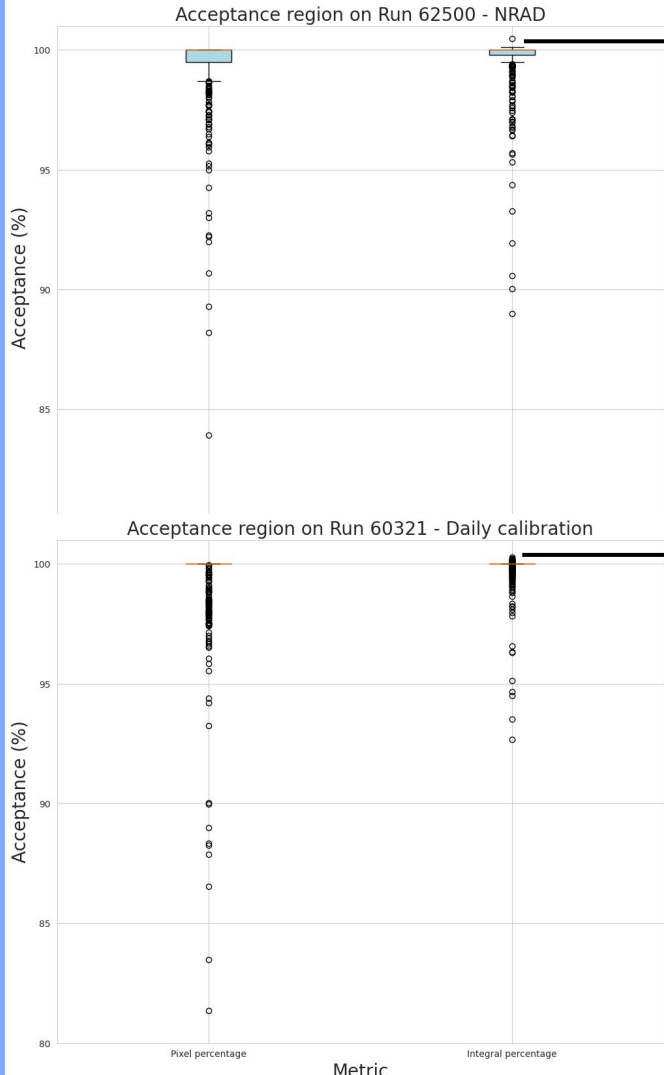
- The **algorithm** needs **~20 ms (CPU<sup>1</sup>)** to **zero all the pixels not around centroids**.
  - It highly **depends** on the **number of centroids** present on the images.
- Considering that **gaussian filter** needs **~200 ms** and **~20 ms** on **CPU<sup>1</sup>** and **GPU<sup>2</sup>** respectively, the algorithm is still **quite fast**.

<sup>1</sup>CPU: Notebook01 cloud  
<sup>2</sup>GPU: Tesla T4 google colab



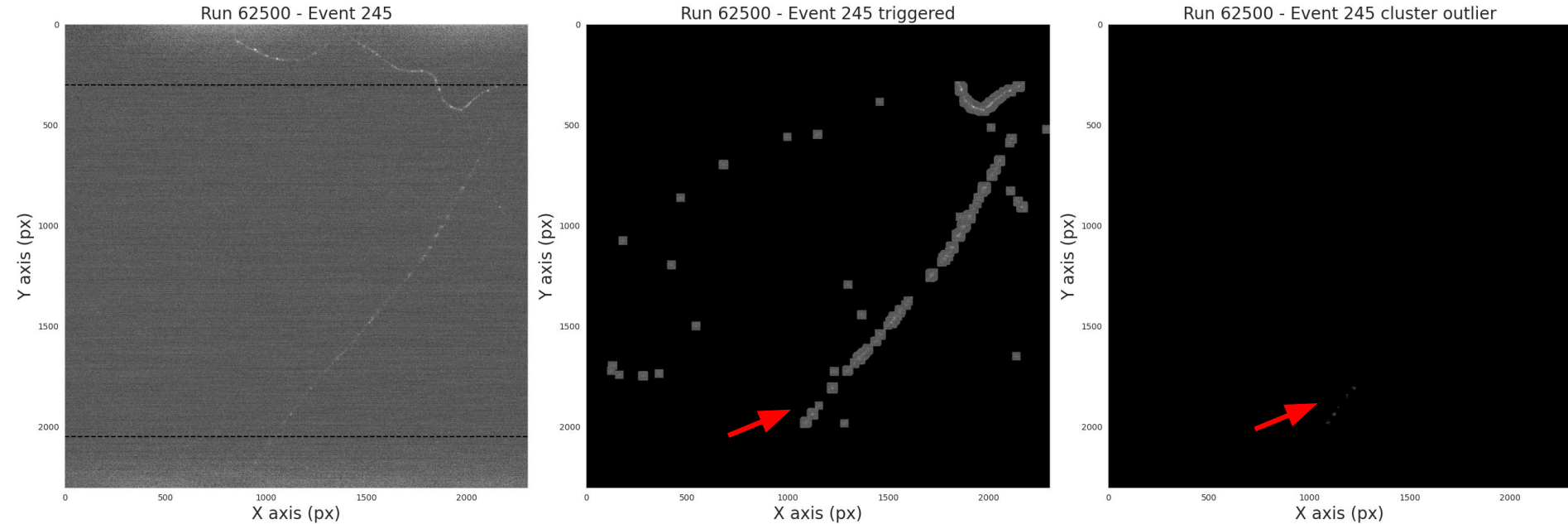
# Real data results (HG)

- **Real data** was used to **estimate** the **algorithm performance** (clusters with more than **2k ADCs** as **target**)
- **NRAD: (99.34±0.08)% pixels** and **(99.58±0.06)% integral** maintained.
- **Daily calibration step2: (99.83±0.03)% pixels** and **(99.96±0.01)% integral** maintained.



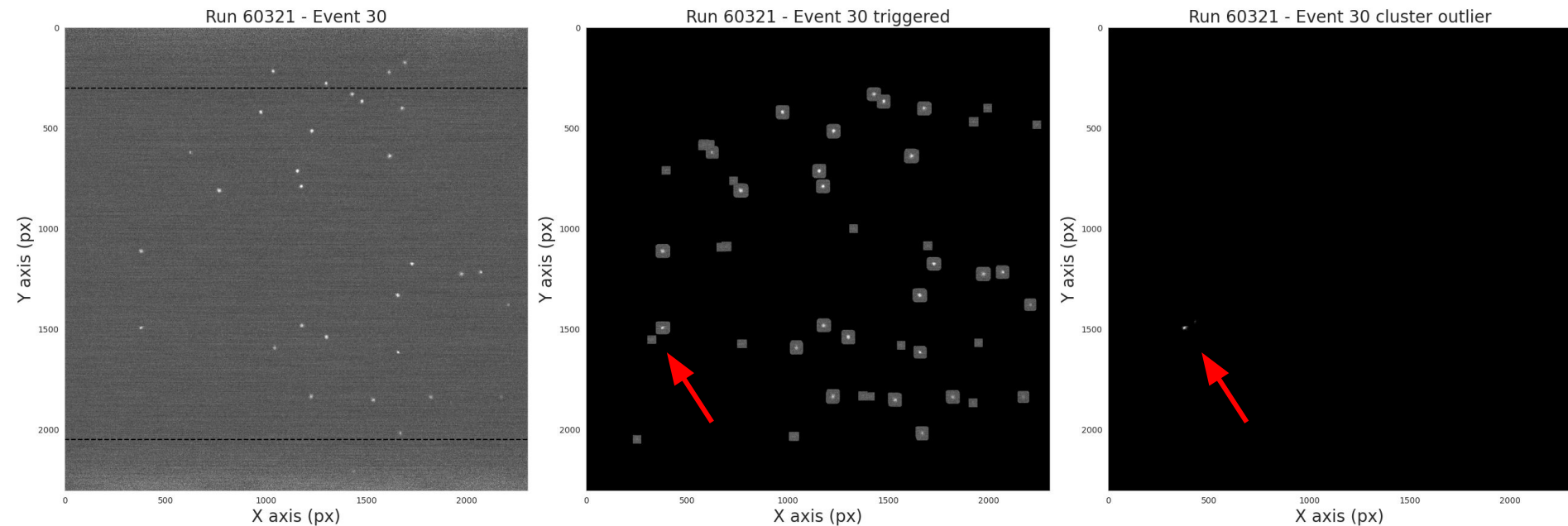
Caused by pedestal subtracted pixels with negative intensity

# Worst case scenarios NRAD



- The **pixel level trigger** maintained **83.92%** and **88.99%** of the **pixels** and **integral** of this **cluster** respectively.

# Worst case scenarios Fe55



- The **pixel level trigger** maintained **78.58%** and **94.66%** of the **pixels** and **integral** of this **cluster** respectively.



## **5. Conclusions**

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# Conclusions

- The analysis using the **new simulation** showed **consistent results** and **proves** that the methods are **resilient**.
- The **pixel level trigger** has a **good potential** to **efficiently save memory** on the **data acquisition**.
  - **Memory reduction factor** of **~40x** on **low energy** simulation.
- It may **detect ~86%** of **0.25 keV (HG)** and **~93%** of **0.75 keV (LG) ER** simulated events.
  - Simulated **ER (HG)** with energies above **3 keV** show **100% efficiency**.
  - **Real data** with more than **2k ADCs counts** are **always detected** maintaining more than **99%** of the **pixels** and **integral**.

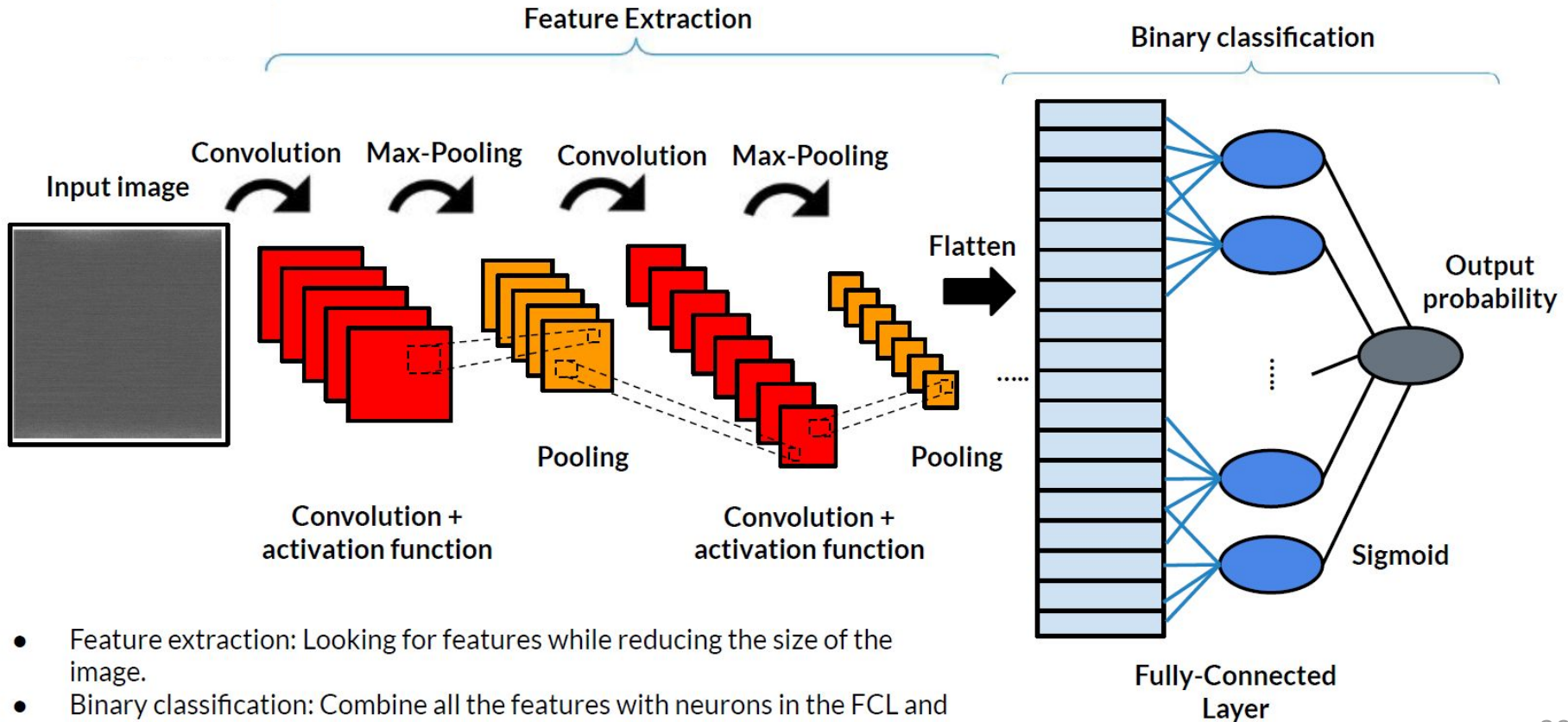
## Next steps

- The **focus** from now on will be on **Quest** data.
  - Recently started to **optimize digitization parameters** for this **camera**.
- **Retrain** the **models** with the **new data**.
- **Test** the **algorithms** on a **data taking** next year.

**Thank you**

# Backup

# CNN architecture



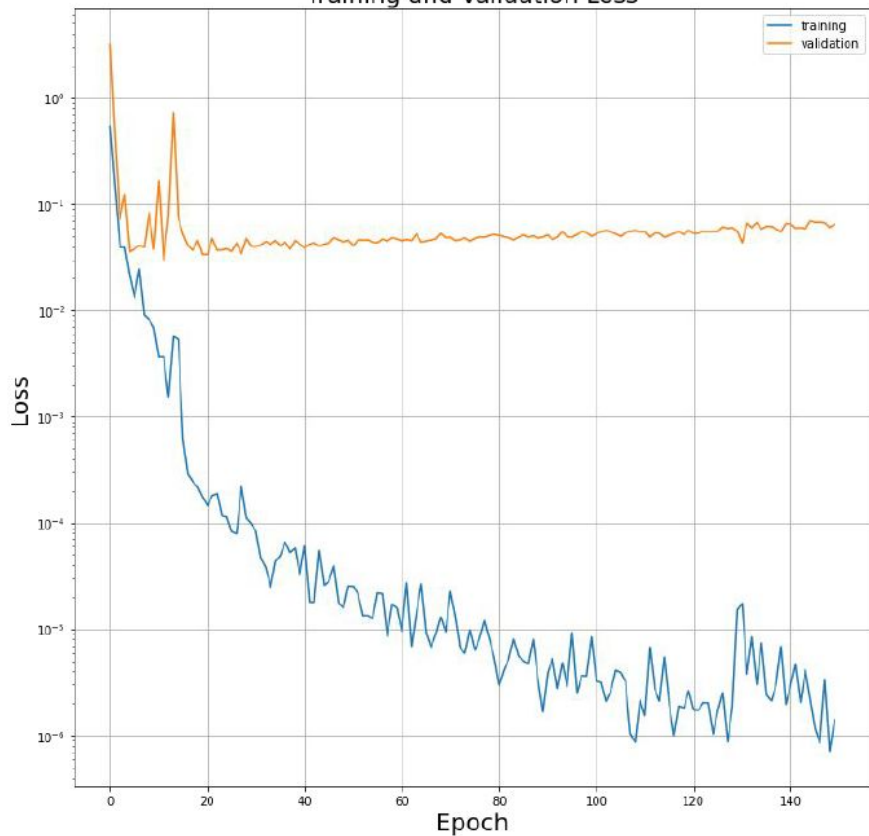
- Feature extraction: Looking for features while reducing the size of the image.
- Binary classification: Combine all the features with neurons in the FCL and classify the input image.

# CNN architecture

- ▷ The input shape of the CNN limits the number of convolutional and max-pooling layers that can be used.
  - An image with 288 ( $2^5 \cdot 3^2$ ) pixels may use up to **7 (5+2)** layers with regular max-pooling.
  - Custom max-pooling layers may be used to increase the number of layers up to 9.
- ▷ Four CNN architectures were selected (number of layers from 6 to 9).
  - The bayesian optimization was used during training.
  - The approach is to select a range of possible hyperparameters (number of filters in each conv layer, neurons on dense layer, etc) and the method will find the optimal values.

# CNN training

Training and Validation Loss



Training and Validation Accuracy

