



# 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** needs **~1.36 Gb** to be stored (Fusion, compressed .mid).
  - A **single day of acquisition** may produce **~266 Gb** of data (Run5 on 26<sup>th</sup> september).
- The motivation of this work was to study algorithms capable of **distinguishing images** 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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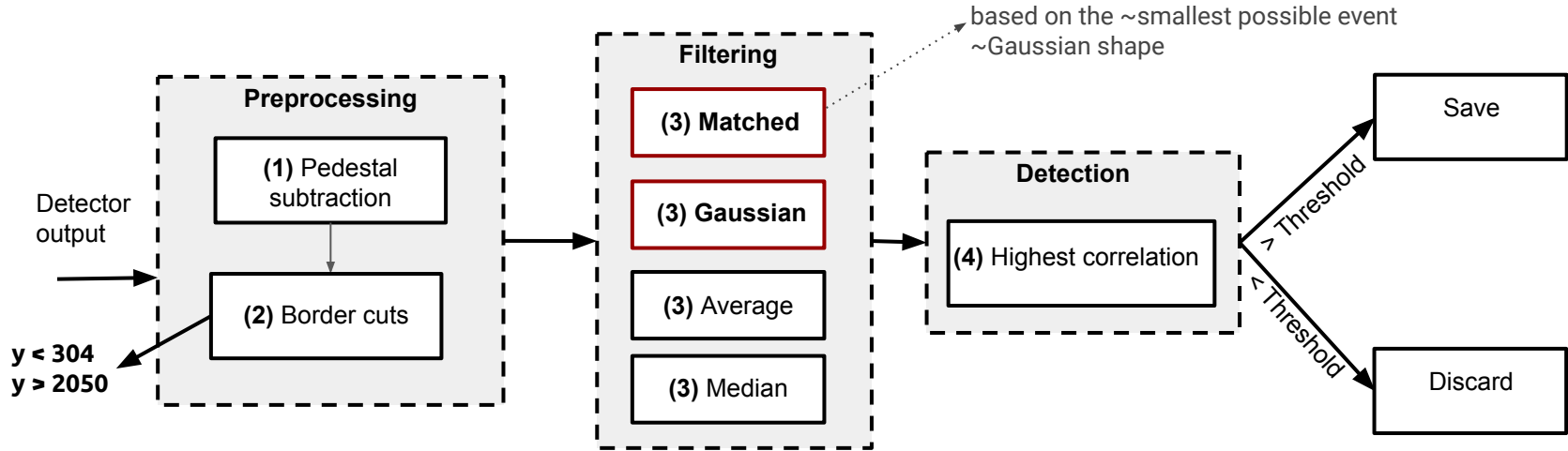
- Two algorithms proposed:
  - **Filtering** based trigger.
  - **CNN** based trigger.
  
- A comparison analysis was done using these two algorithms:
  - Trigger **detection performance**.
  - Reconstruction comparison.
  - **Processing time**.



## **2. Algorithms**

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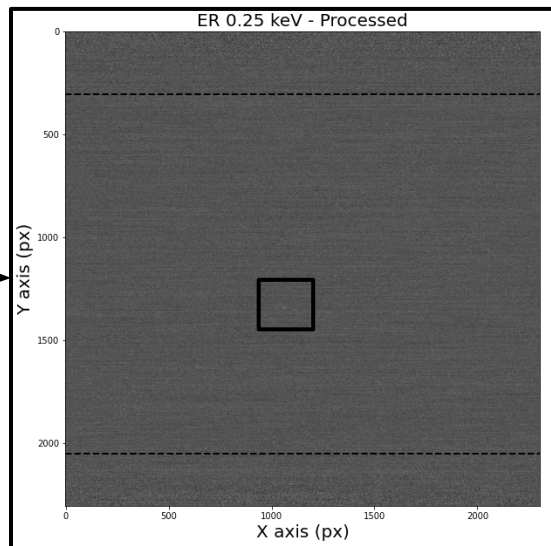
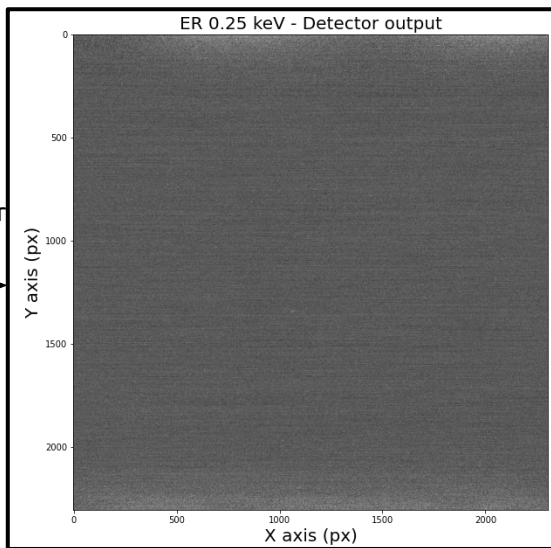
# Filtering based trigger



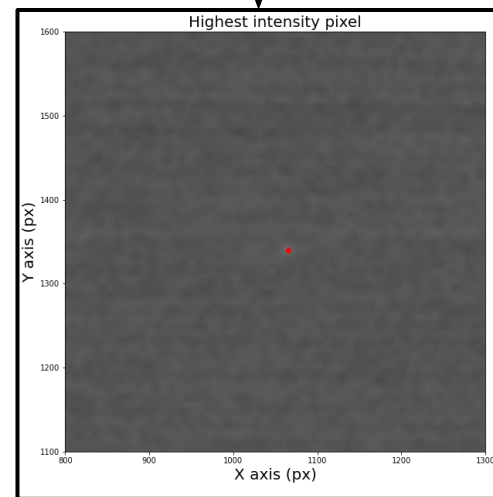
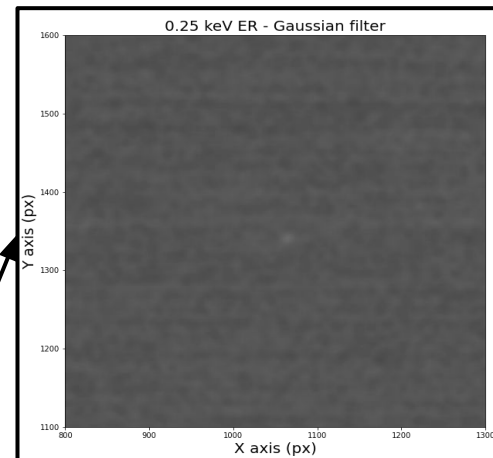
Filter parameters and detection threshold  
selected based on training data

# Filtering based trigger

Detector output

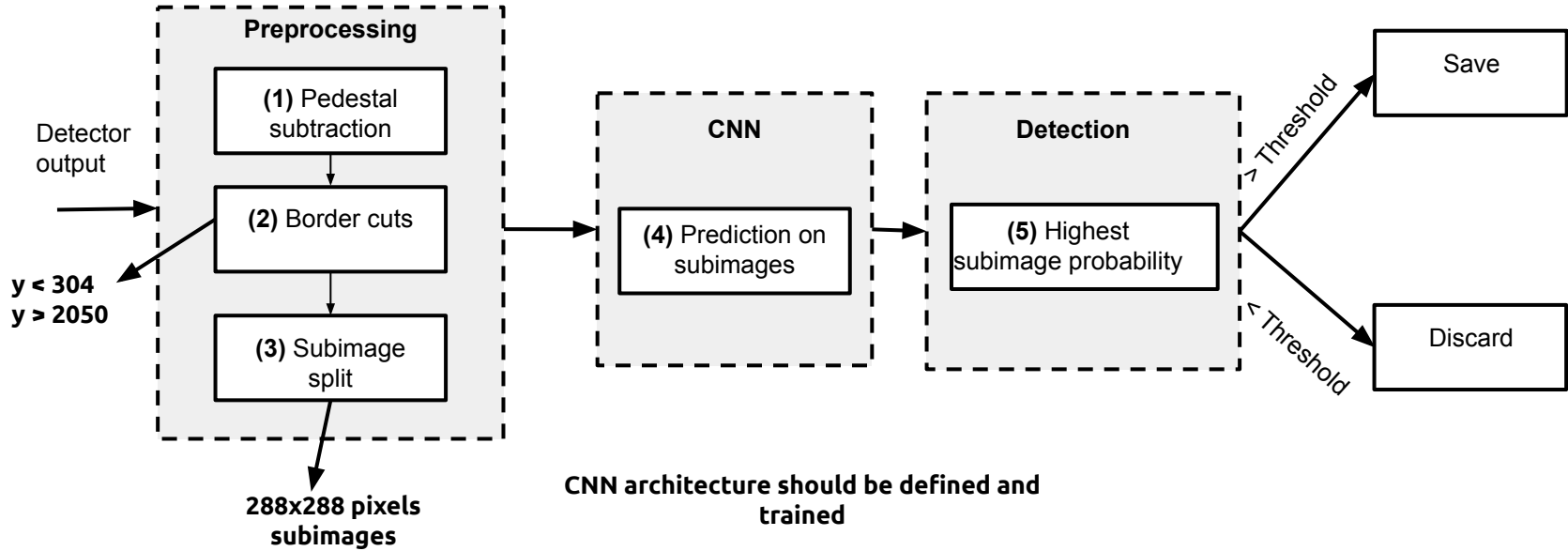


**Pedsub + Border cuts**

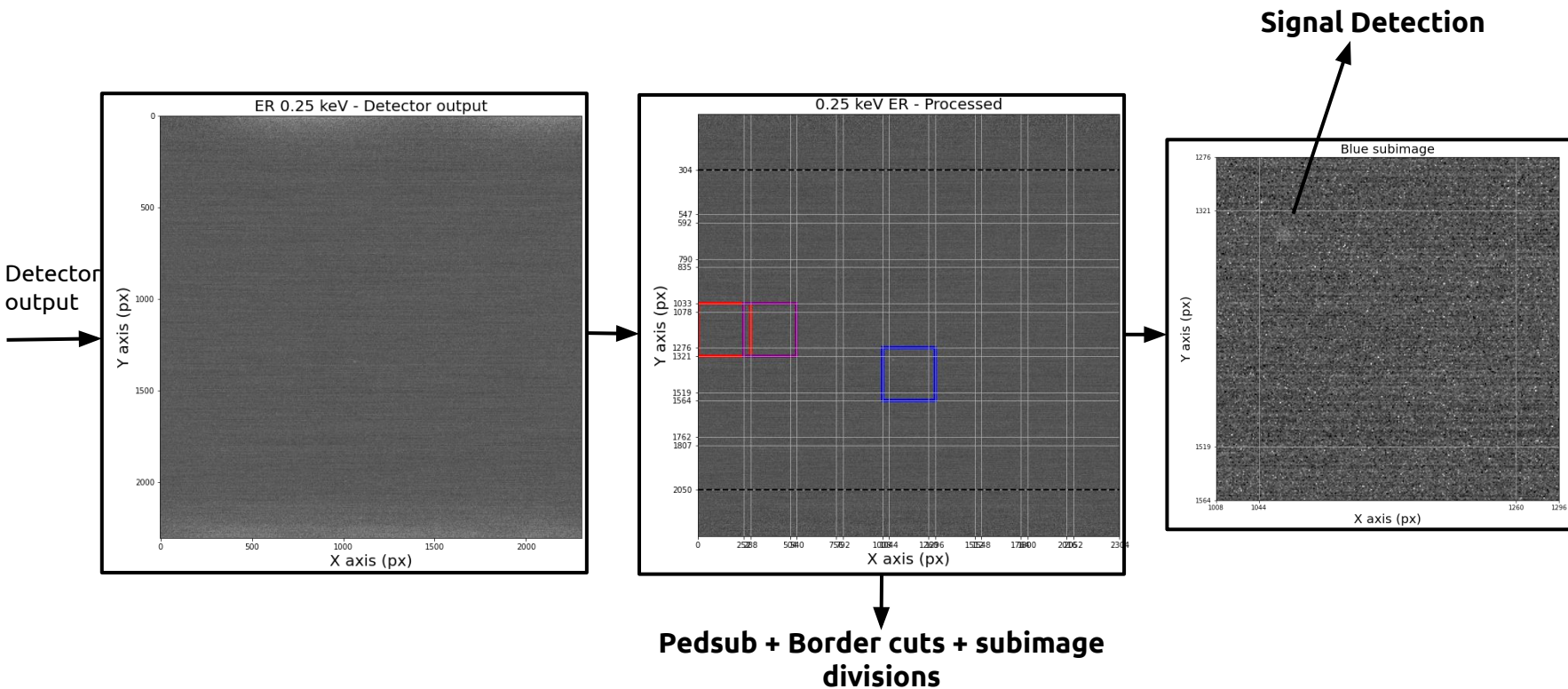




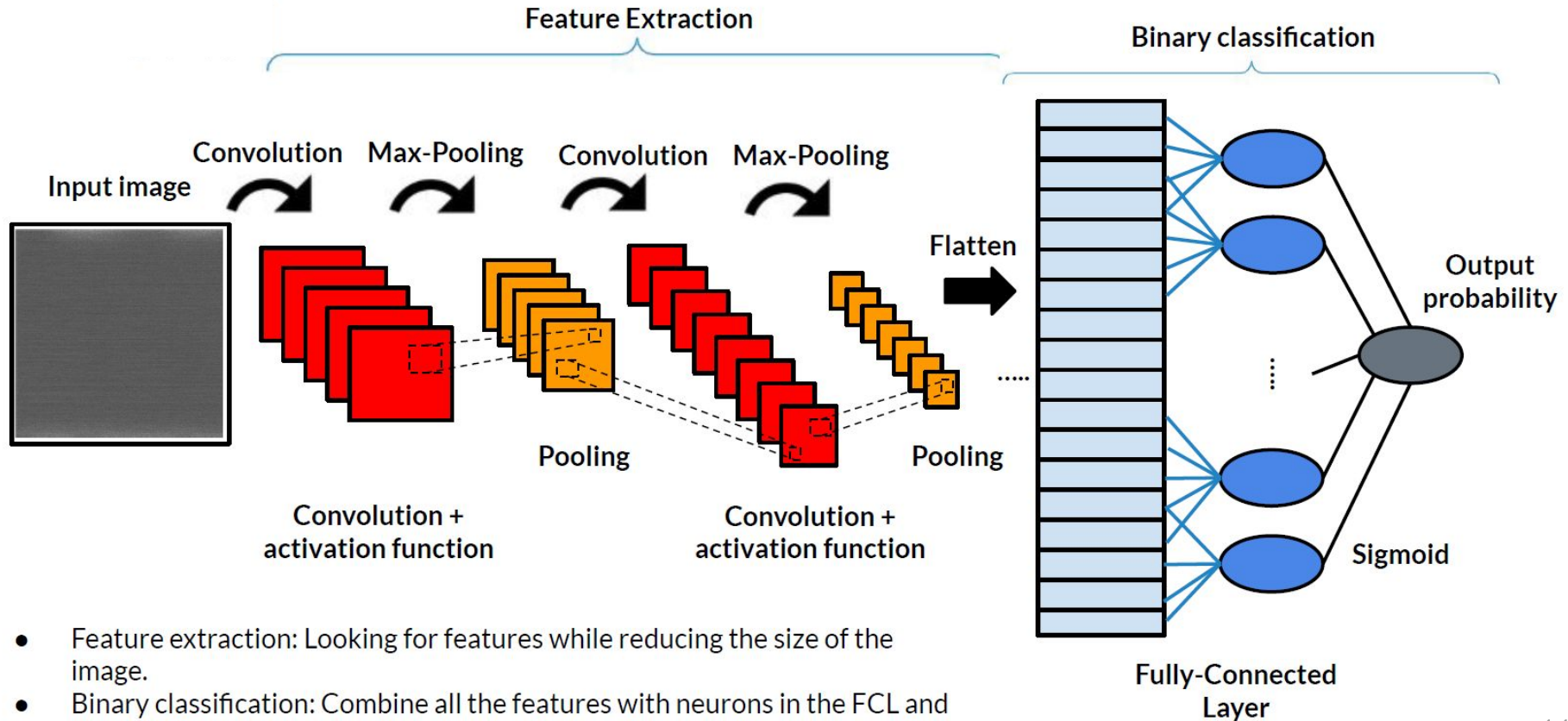
# CNN based trigger



# CNN based trigger



# 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.



## 3. Development

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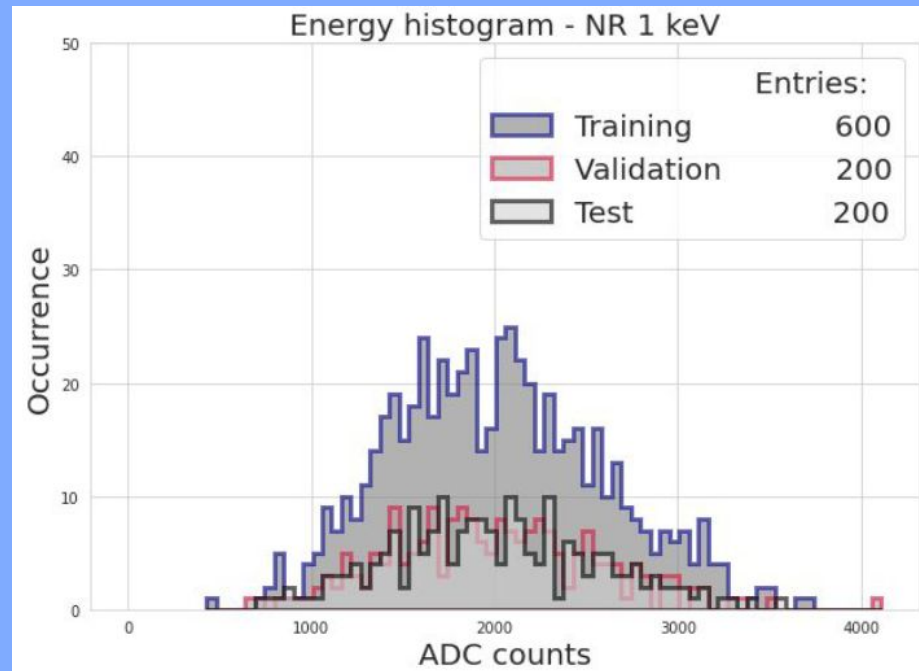
# Datasets

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- **Training:**
  - Noise dataset: 600 images from pedestals runs (Run4 underground).
  - ER and NR signal simulation: 600 images each containing 0.25-1 keV signals added to pedestal runs (different from noise dataset).
- **Validation:**
  - Noise dataset: 200 images from pedestal runs.
  - ER and NR signal simulation: 200 images each containing 0.25-1 keV signals.
- **Test:**
  - Same configuration as validation.

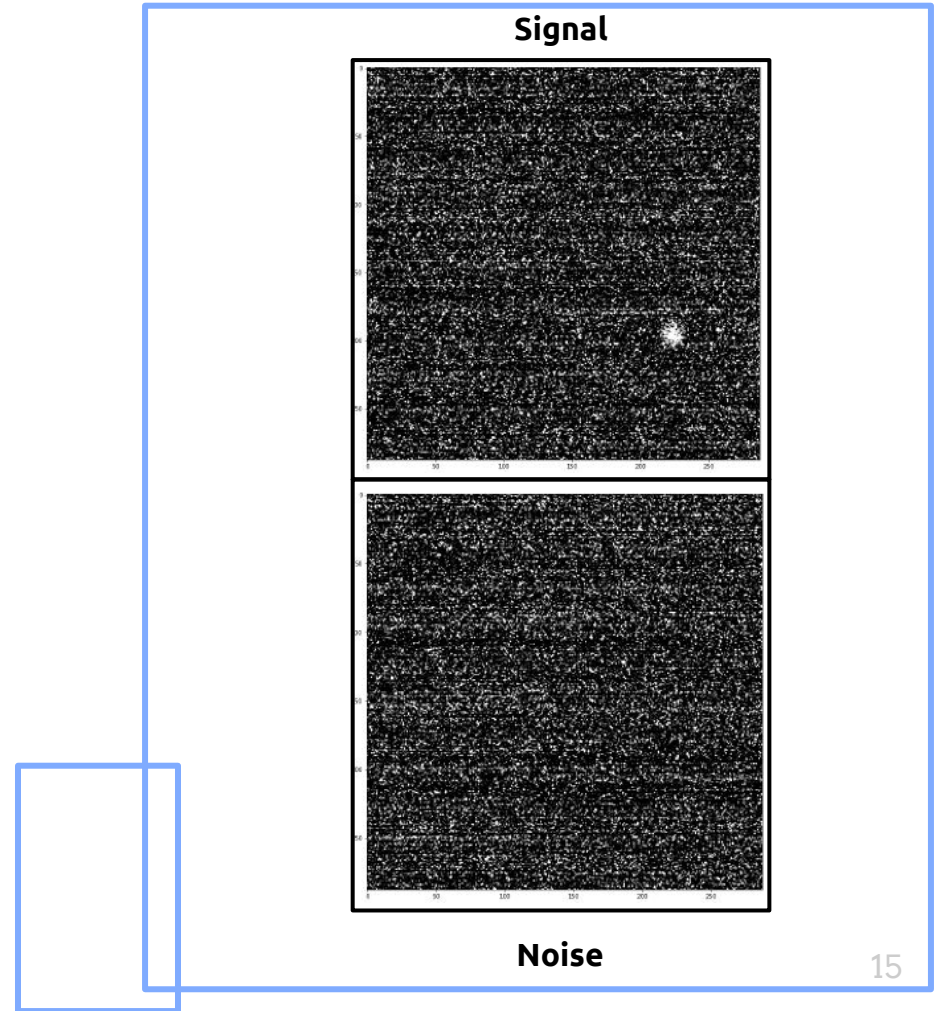
# Datasets

- The signal simulation was **divided** considering the **balance in ADC counts** across the three datasets.
- This prevents the **data split** from **influencing** the results.



# CNN training

- Both **ER** and **NR** were used **together** during the **CNN training** using **data augmentation**.
  - The signal was **randomly rotated** and **placed** in a position among the noise.
- **4800 images** with **288x288** pixels were used on **CNN training** and **1600** on **validation**.
  - Every signal from the split was **used twice**.
  - The **noise patch** used was always **different**.
- The best result was achieved by using **0.5 keV** signals on training.
  - 0.25 keVs signals generally led to overfitting.





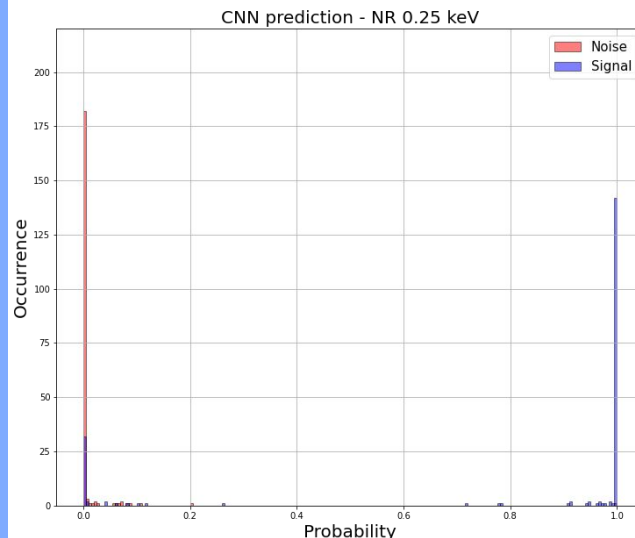
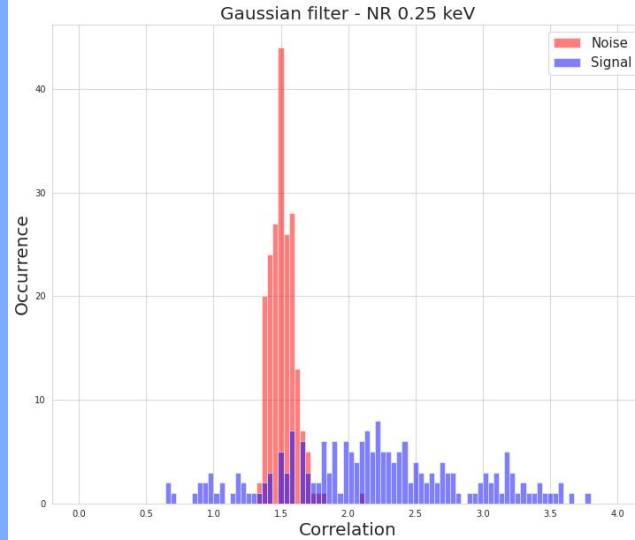
## 4. Results

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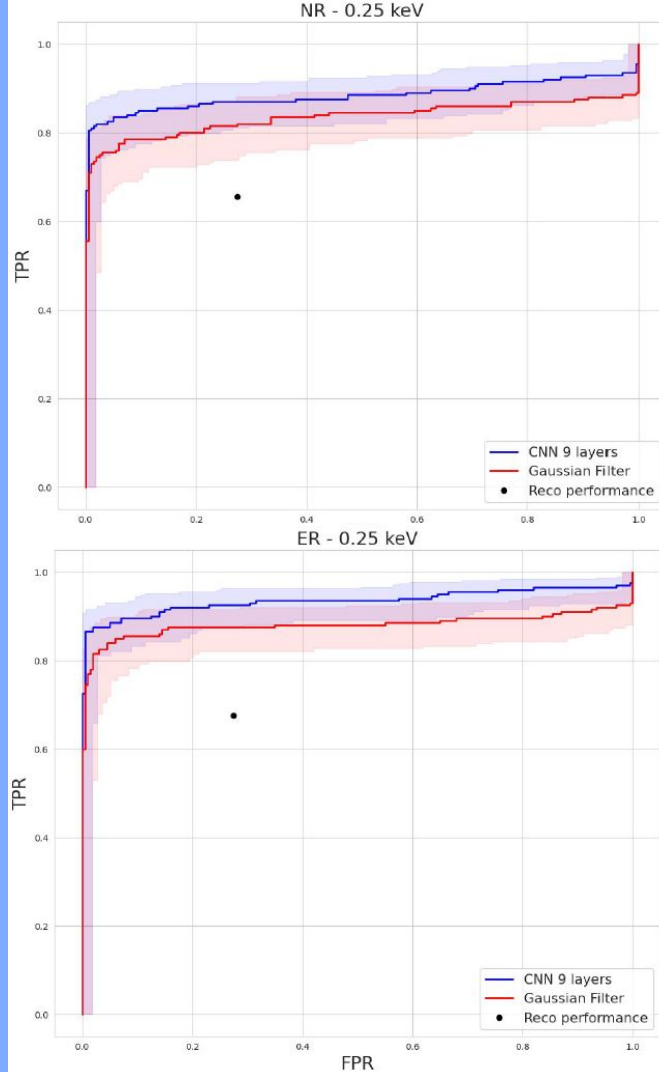
# Detection performance

- Applying the trigger algorithms on the test dataset results in **two distributions**.
  - The **Gaussian filter** method **output** is a **correlation**.
  - The **CNN output** is a **probability** (more interpretable)
- These distributions may be used on **ROC curves** to evaluate the results.
  - All possible thresholds are used to measure the true positive rate (**TPR**) and false positive rate (**FPR**).
  - **TPR** is analogue to **signal detection**.
  - **FPR** is analogue to **false alarm**.



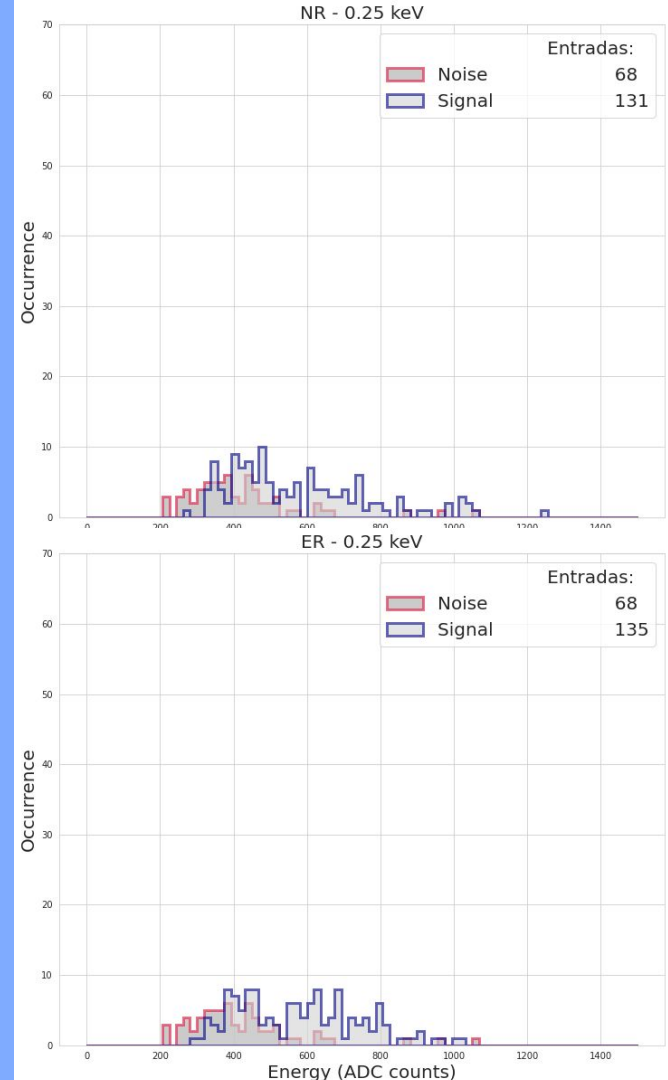
# Detection performance

- The **Gaussian filter** may **detect ~80%** of the **0.25 keV NR** and **ER** events with a **~10% false alarm**.
- The **CNN** may **detect ~80%** of the **0.25 keV NR** and **ER** events with a **~0.5% false alarm**.
- Both methods **outperform** the **reconstruction** in **detecting 0.25 keV** events.
- **All methods** can easily **detect** energies **above 0.5 keV**.



# Reconstruction

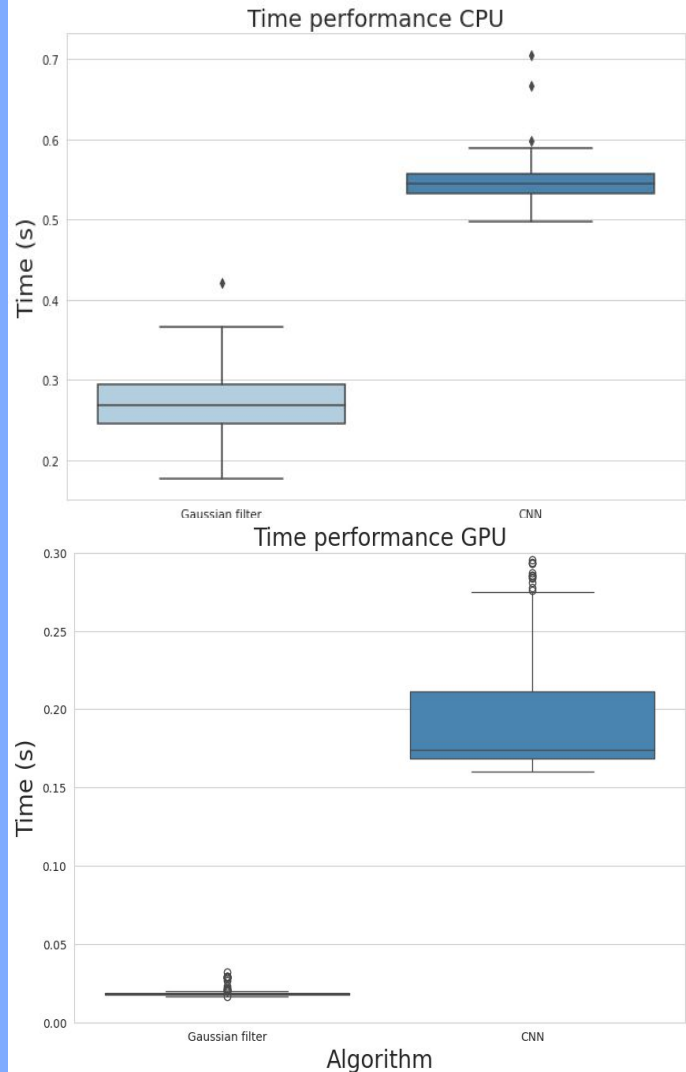
- The reconstruction code found **68 noise clusters** on **55 images (~27.5% false alarm)** on the test dataset.
- The reconstruction detected **131 NR (~65.5% detection)** and **135 ER (~67.5% detection)** events with **0.25 keV**.
- **All events** found by the **reconstruction** were also **detected** by the **trigger algorithms**.



# Processing time

- The **Gaussian filter** and **CNN** need **~0.25** and **0.55 seconds** to analyse one image using **CPU<sup>1</sup>** respectively.
- The **Gaussian filter** and **CNN** need **~0.02** and **0.2 seconds** to analyse one image using **GPU<sup>2</sup>** respectively.
- A **higher detection performance** needs to be **compensated** with a **slower processing time**.

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





## **5. Conclusions**

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# Conclusions

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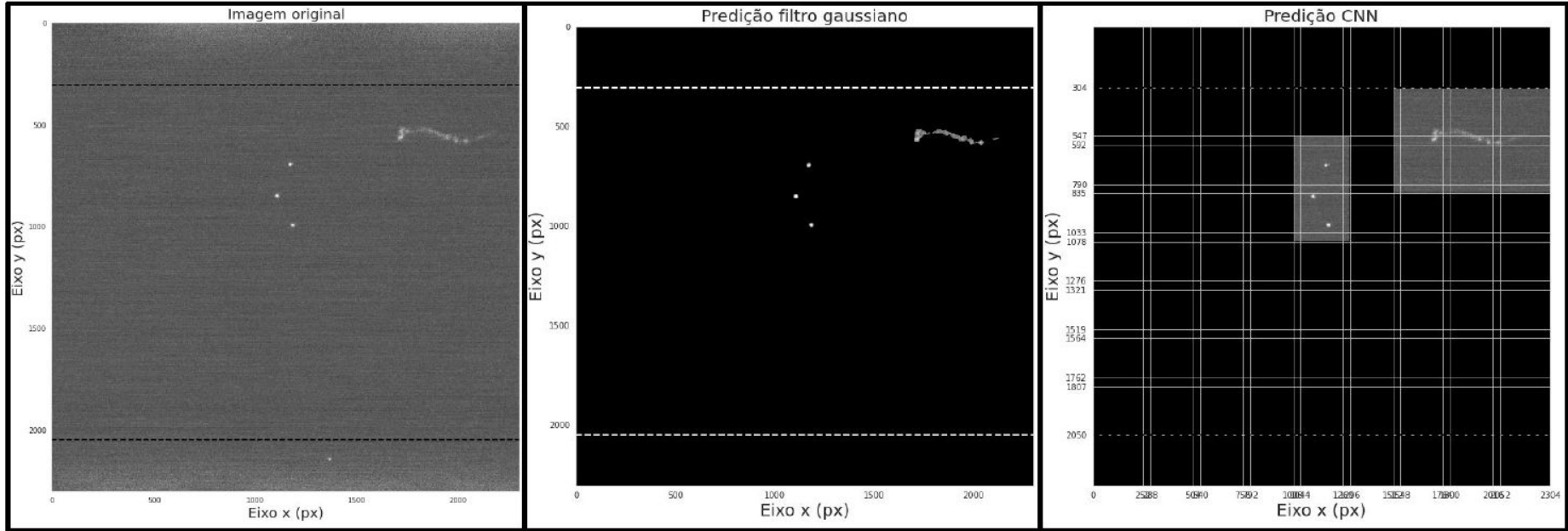
- The proposed algorithms may **detect ~80%** of the **0.25 keV NR** and **ER simulated events** with a **small false alarm** ratio.
  - **Gaussian filter** with **10% false alarm** (**20 out of 200** pedestal images **misclassified**).
  - **CNN** with **0.5% false alarm** (**1 out of 200** pedestal images **misclassified**).
- The proposed algorithms may **detect ~100%** of the events **above 0.5 keV**.
- The **CNN needs a GPU** to have a **proper margin time** to analyse an image considering the current exposure time, whereas the **Gaussian filter** may be implemented with a **CPU**.
- **All the events** detected by the **reconstruction** were easily detected by the **proposed algorithms**.

# Next steps

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- Study methods to simplify the CNN model (on going).
  - **Bit reduction, weight combination, pruning and vectorization.**
- Test the CNN on the DAQ machine.
  - **GPU: Quadro RTX 5000.**
- Test popular CNN architectures such as AlexNet, GoogleLeNet, Unet with adaptations.
- Three possible approaches for the trigger:
  - Save the entire image.
  - Save subparts of the images.
  - Retrain the CNN to reject also natural radioactivity.

# Next steps





**Thank you**

# Credits

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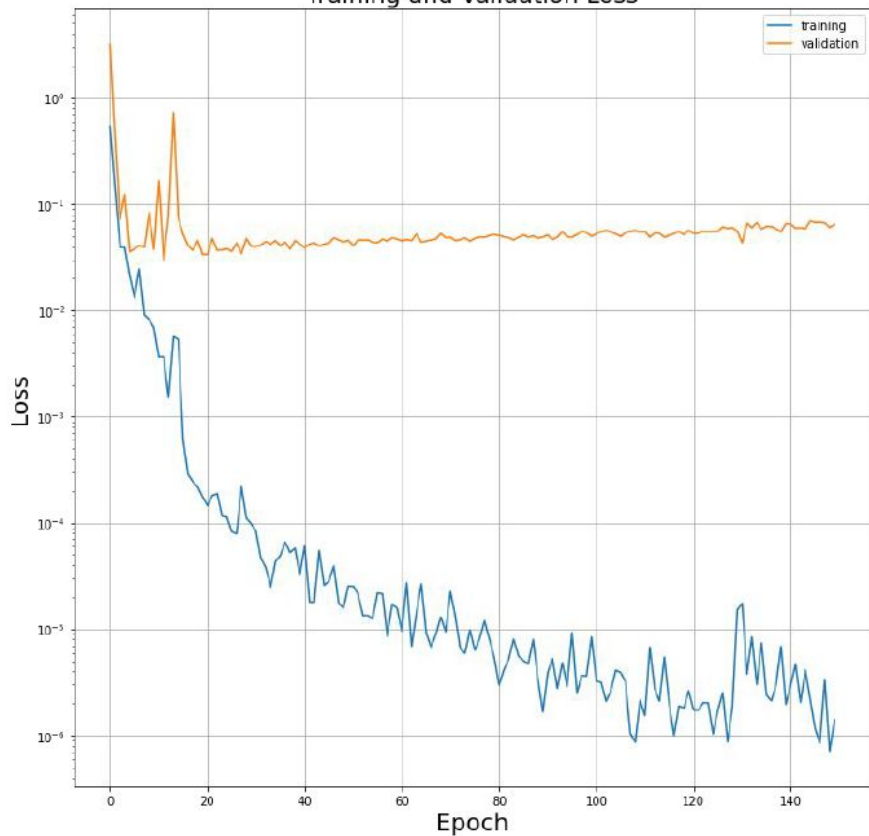
# Backup

# CNN architecture

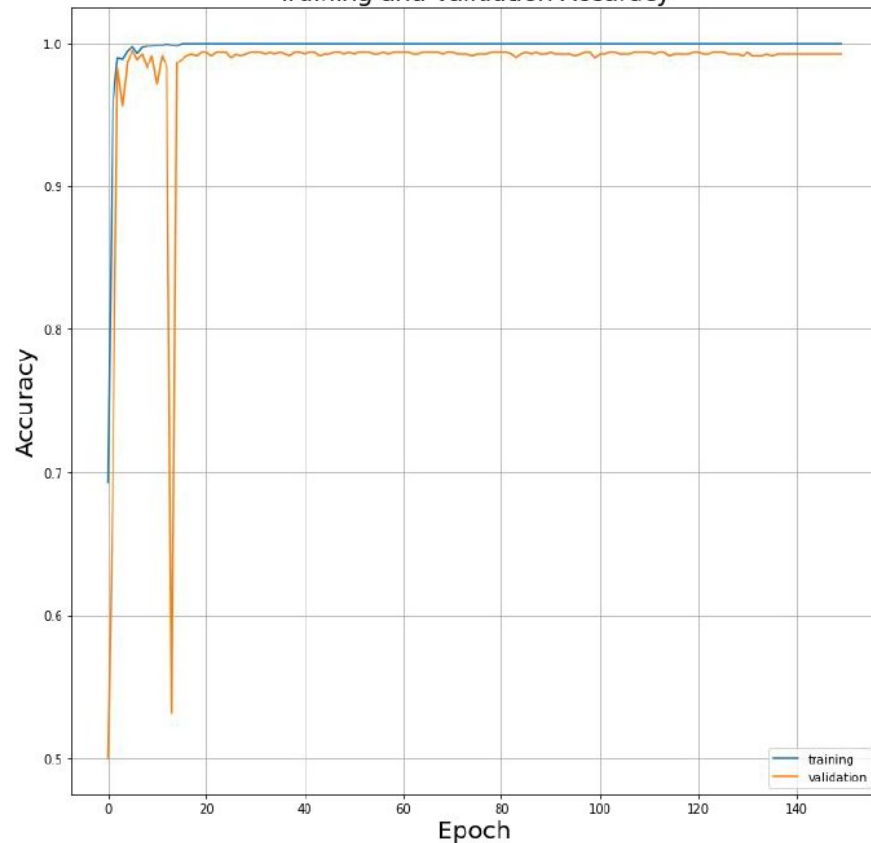
- ▷ The input shape of the CNN limits the number of convolutional and max-pooling layers that can be used.
  - An image with 288 ( $2^5 \cdot 3^2$ ) pixels may use up to **7 (5+2)** layers with regular max-pooling.
  - Custom max-pooling layers may be used to increase the number of layers up to 9.
- ▷ 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



# CNN 0.5 keV

