Using artificial intelligence in the reconstruction of signals from the PADME electromagnetic calorimeter

Kalina Stoimenova
Faculty of Physics, Sofia University

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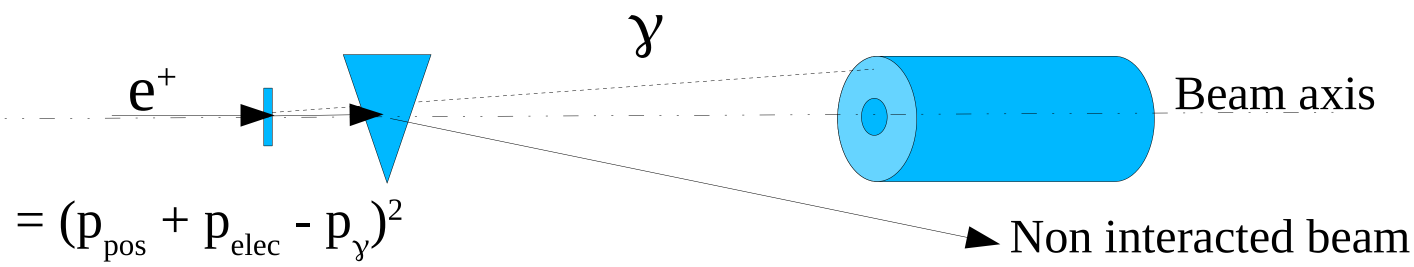
Outline

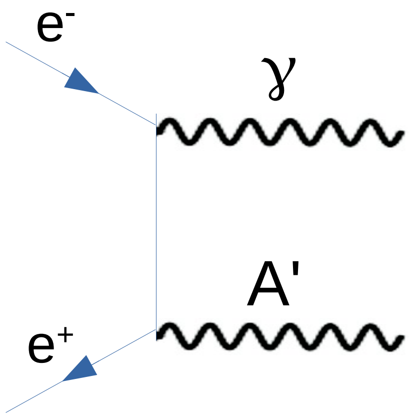
- The PADME experiment
- Signal simulation
- Signal description using neural networks
- DNN for signal parameter reconstruction
- Conclusion

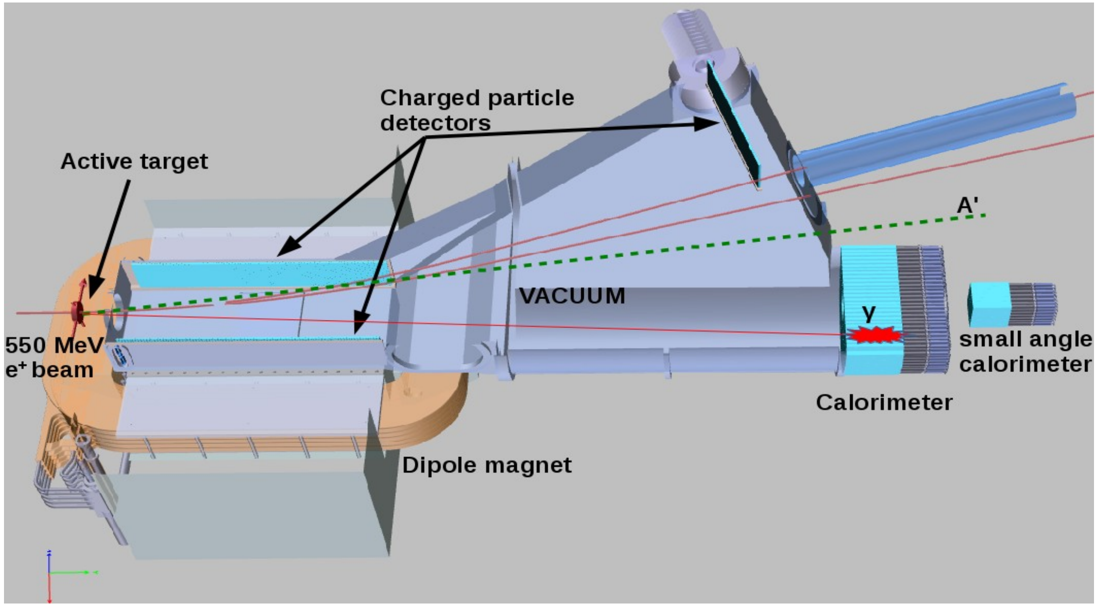
The PADME Experiment

Positron Annihilation into Dark Matter Experiment



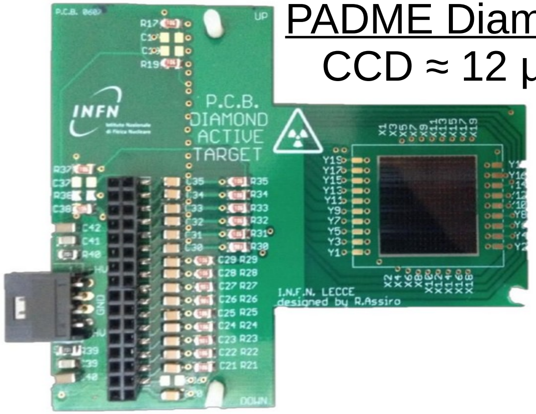
$$M_{miss}^2 = (p_{pos} + p_{elec} - p_{\gamma})^2$$



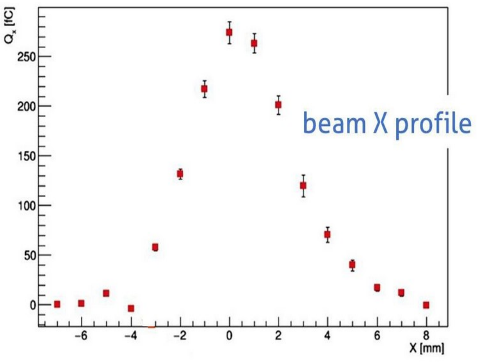


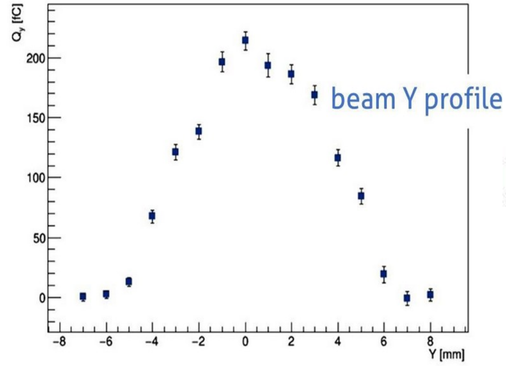
- Small scale fixed target experiment
  - e^+ @ Frascati Beam Test Facility
  - Solid state target
  - Charged particles detectors
  - Calorimeter
  - Beam monitoring system

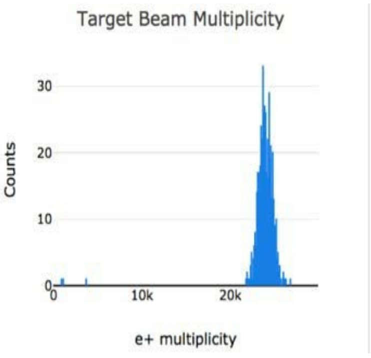
Active target

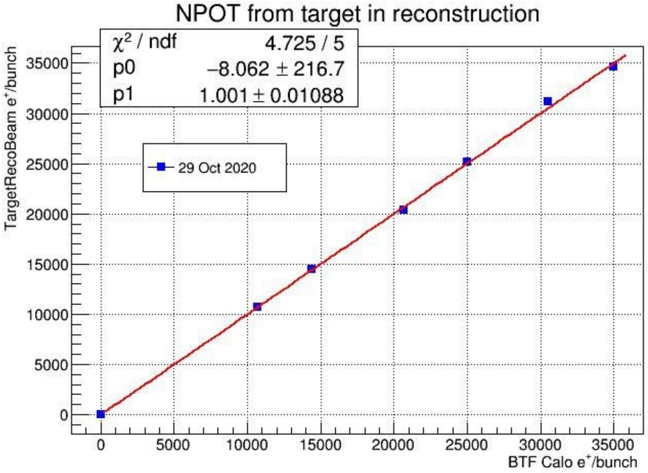


PADME Diamond
CCD ≈ 12 μm



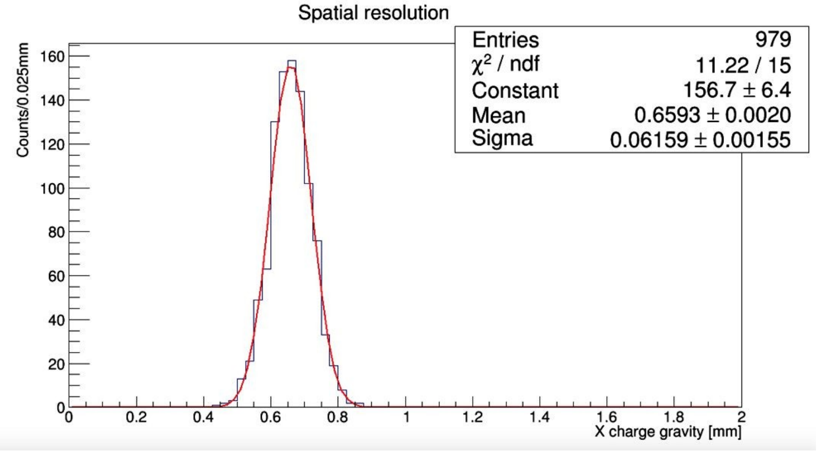




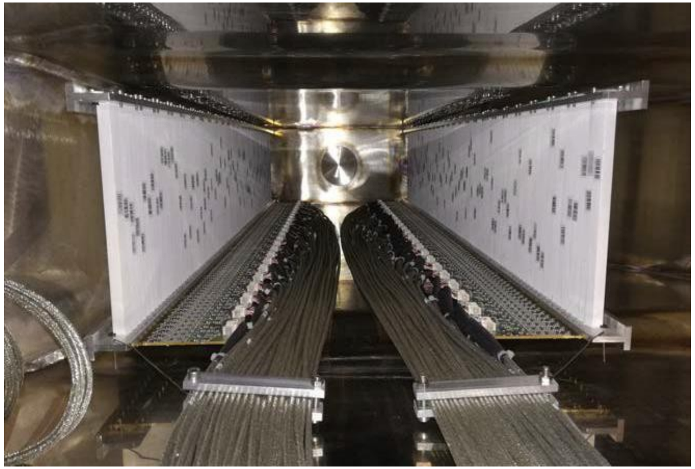


Polycrystalline diamonds

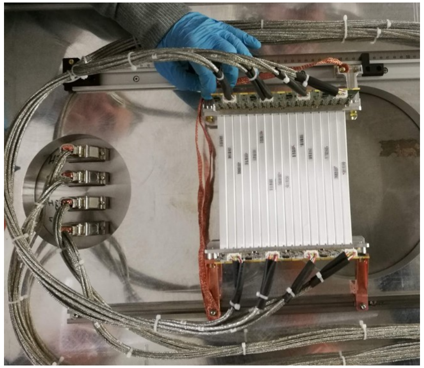
- 100 μm thickness:
- 16 × 1 mm strip and X-Y readout in a single detector
- Graphite electrodes using excimer laser



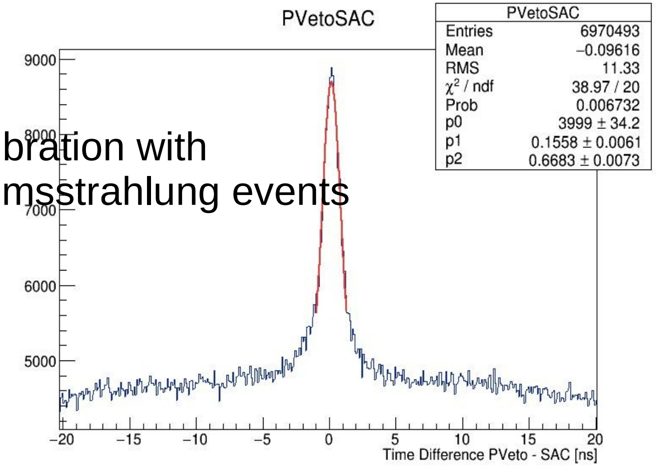
Charged particle detectors



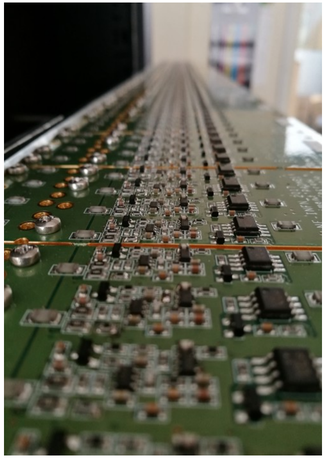
- Three sets of detectors detect the charged particles from the PADME target (at E_{beam} = 550 MeV):
  - **PVeto**: positrons with 50 MeV < p_{e+} < 450 MeV
  - **HEPVeto**: positrons with 450 MeV < p_{e+} < 500 MeV
  - **EVeto**: electrons with 50 MeV < p_{e+} < 450 MeV
- 96 + 96 (90) + 16 (x2) scintillator-WLS-SiPM RO channels
- Segmentation provides momentum measurement down to ~ 5 MeV resolution



Time calibration with Bremsstrahlung events

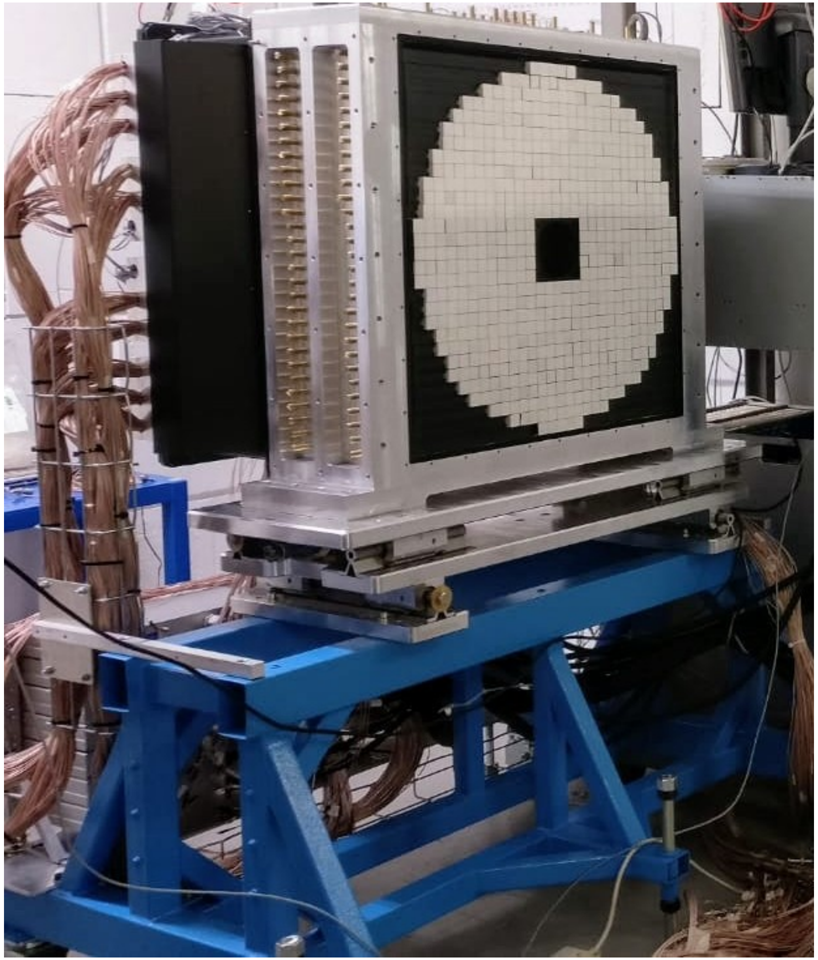


- Custom SiPM electronics, Hamamatsu S13360 3 mm, 25μm pixel SiPM
- Differential signals to the controllers, HV, thermal and current monitoring

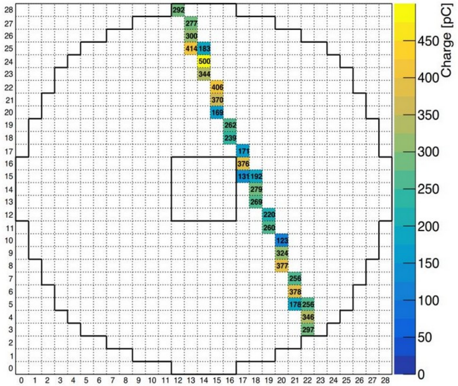


- Online time resolution: ~ 2 ns
- Offline time resolution after fine T_0 calculation – better than 1 ns

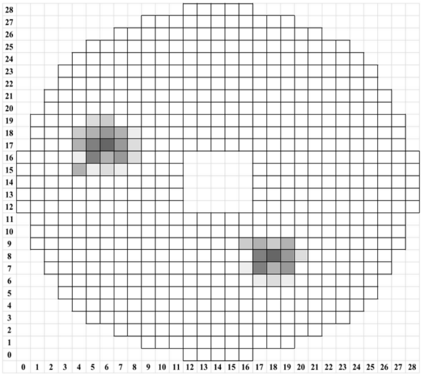
PADME calorimeter



Muon track

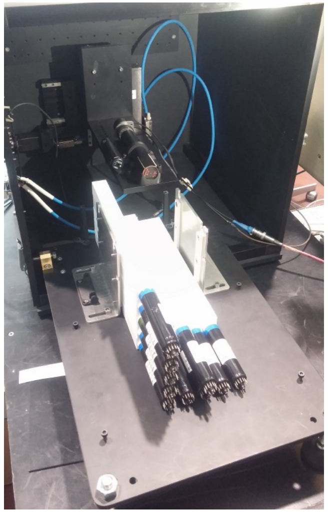


Two photon showers

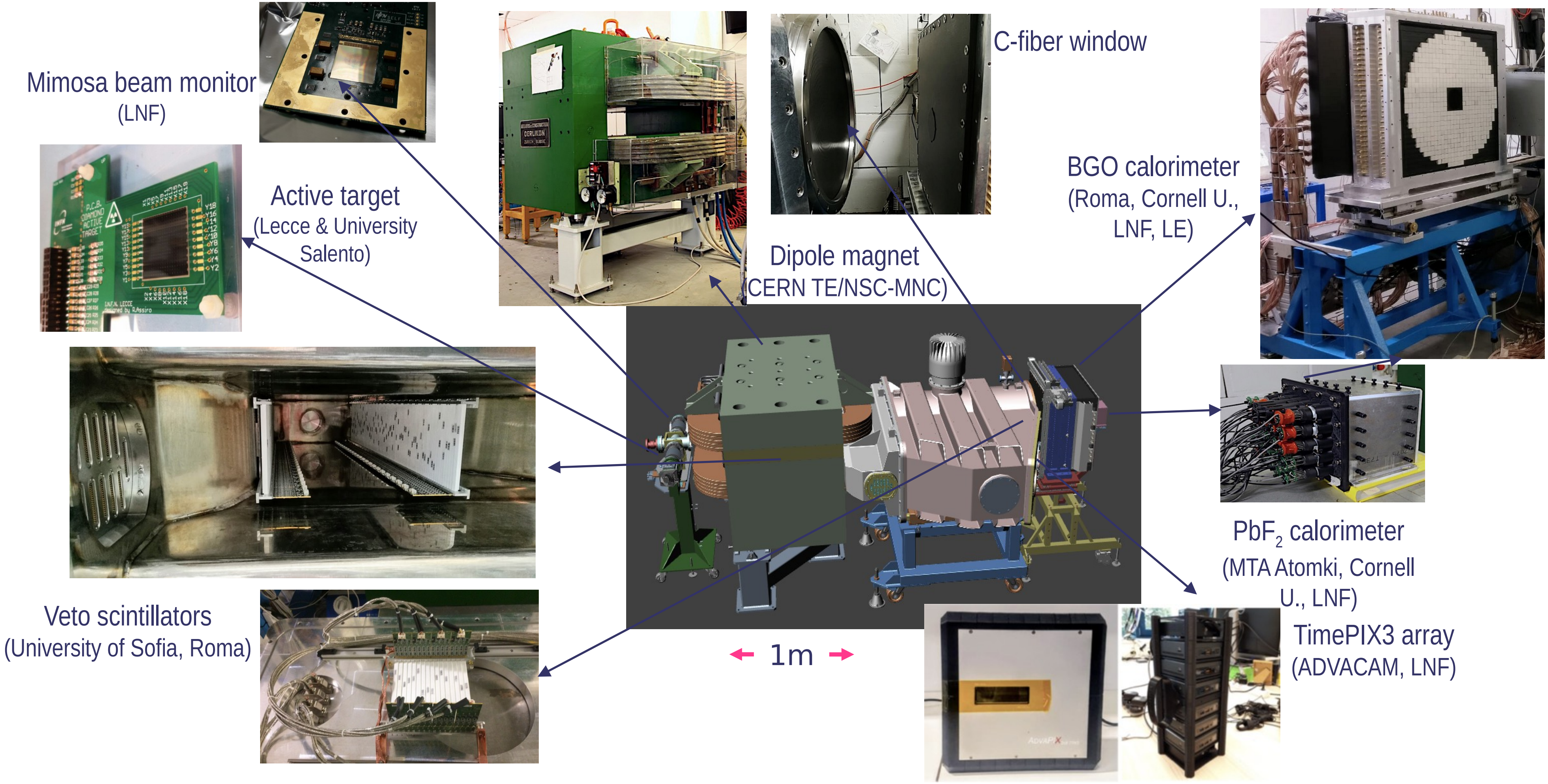


ECAL: The heart of PADME

- 616 BGO crystals, 2.1 x 2.1 x 23 cm^3
- BGO covered with diffuse reflective TiO_2 paint
  - additional optical isolation:
    50 – 100 µm black tedlar foils
- Scintillation light decay time – O(300 ns)
- HZC 1912 PMTs
- Calibrated with ^{22}Na source and cosmics

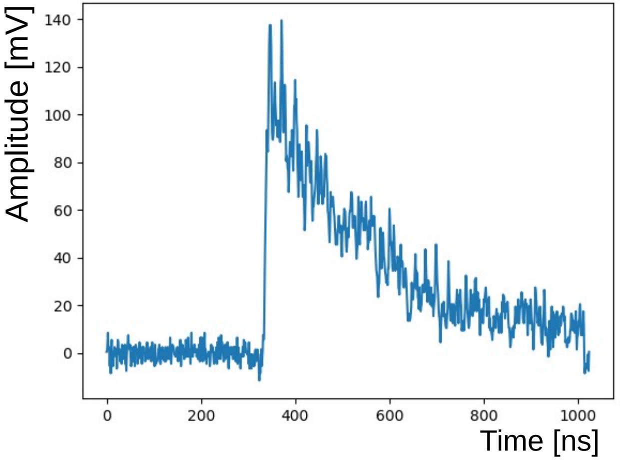


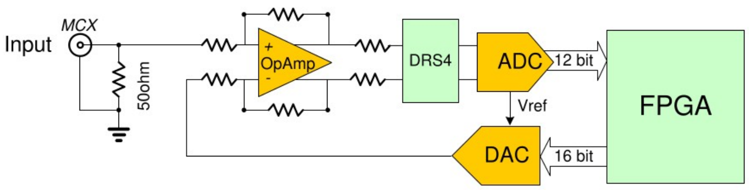
PADME

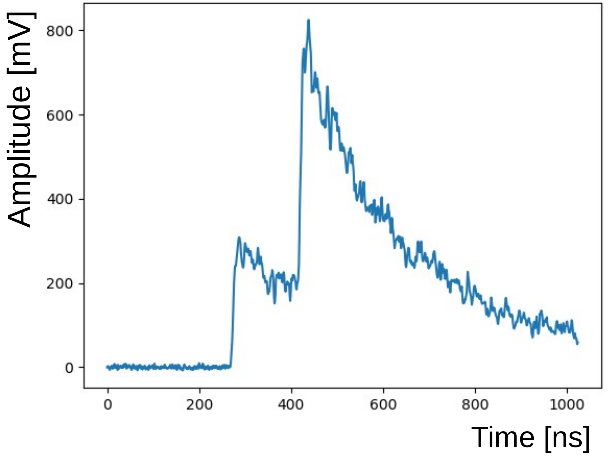

Mimosa beam monitor
(LNF)
Active target
(Lecce & University
Salento)
C-fiber window
Dipole magnet
(CERN TE/NSC-MNC)
BGO calorimeter
(Roma, Cornell U.,
LNF, LE)
PbF2 calorimeter
(MTA Atomki, Cornell
U., LNF)
TimePIX3 array
(ADVACAM, LNF)
Veto scintillators
(University of Sofia, Roma)
1m

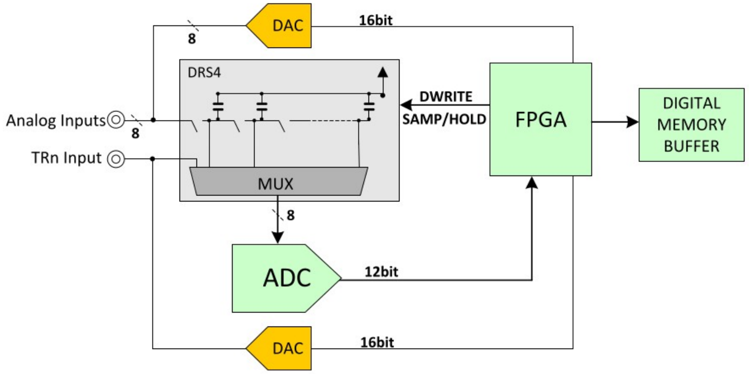
Calorimeter readout system

- CAEN V1742 digitizer, DRS4 chip operated at 1 GS/s
- Storage capacitor array, 1024 samples maximum
- Recording the complete waveform upon a beam based trigger signal
- Common choice for almost all PADME detectors



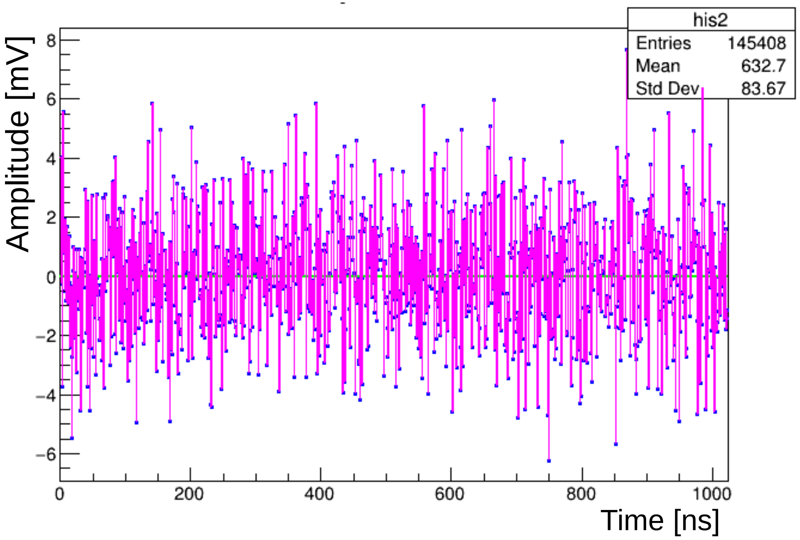


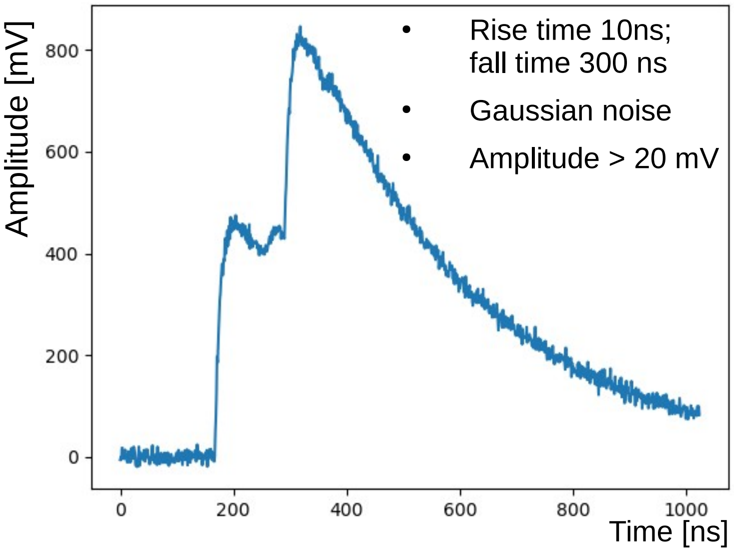




Signal simulation

- Generation of noise + several waveforms (predefined maximum number)
- Noise taken as white noise – gaussian amplitude at random time





- Pulse generation – currently taken as difference between two exponents

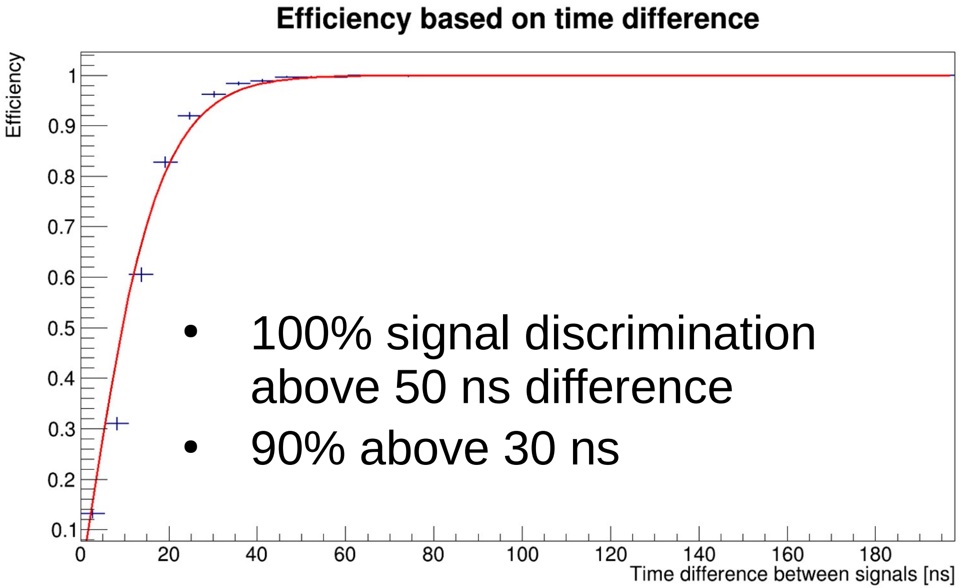
$$A(t) = A_0\left(e^{-\frac{t}{\tau_1}} - e^{-\frac{t}{\tau_2}}\right) = A_0 e^{-\frac{t}{\tau_1}}\left(1 - e^{-\frac{t}{\tau}}\right) \quad , \quad \tau = \frac{\tau_2 \tau_1}{\tau_1 - \tau_2}$$

- τ_1 – decay time of the signal

NN signal description

Classification NN

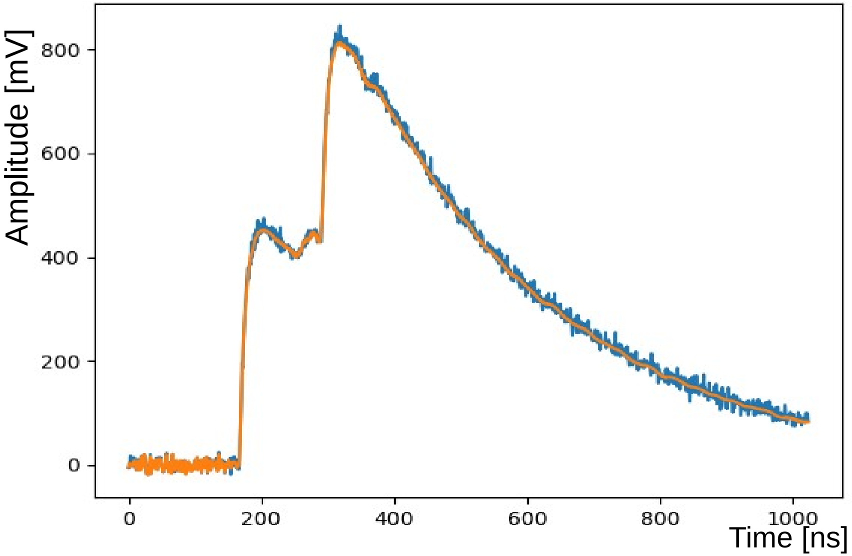
- AI to identify the number of pulses in a waveform
- Simple output – up to five pulses
- Trained on 100 000 events



- 100% signal discrimination above 50 ns difference
- 90% above 30 ns

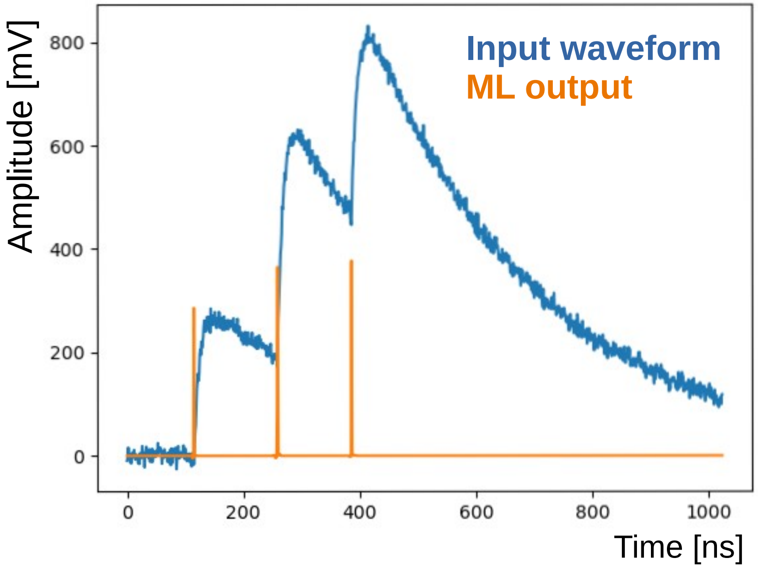
Signal and noise description

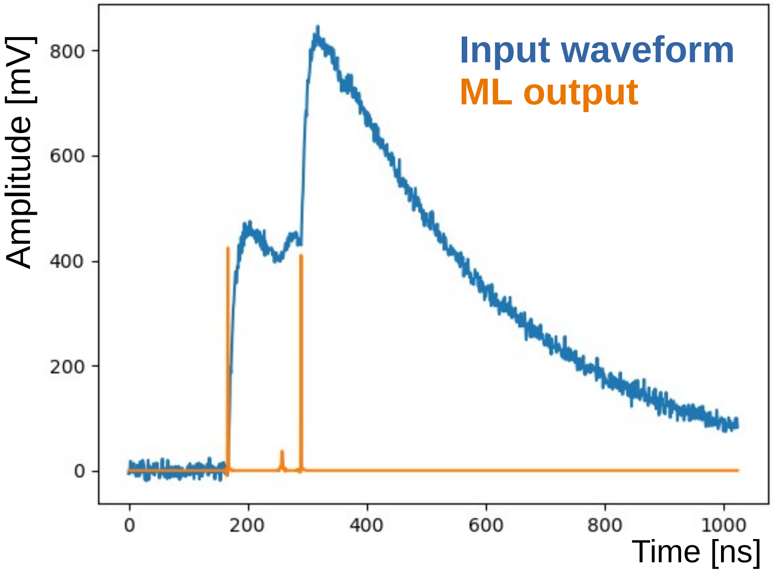
- Convolutional autoencoder
- Input and output size 1024
- Noise in the signal regions significantly suppressed



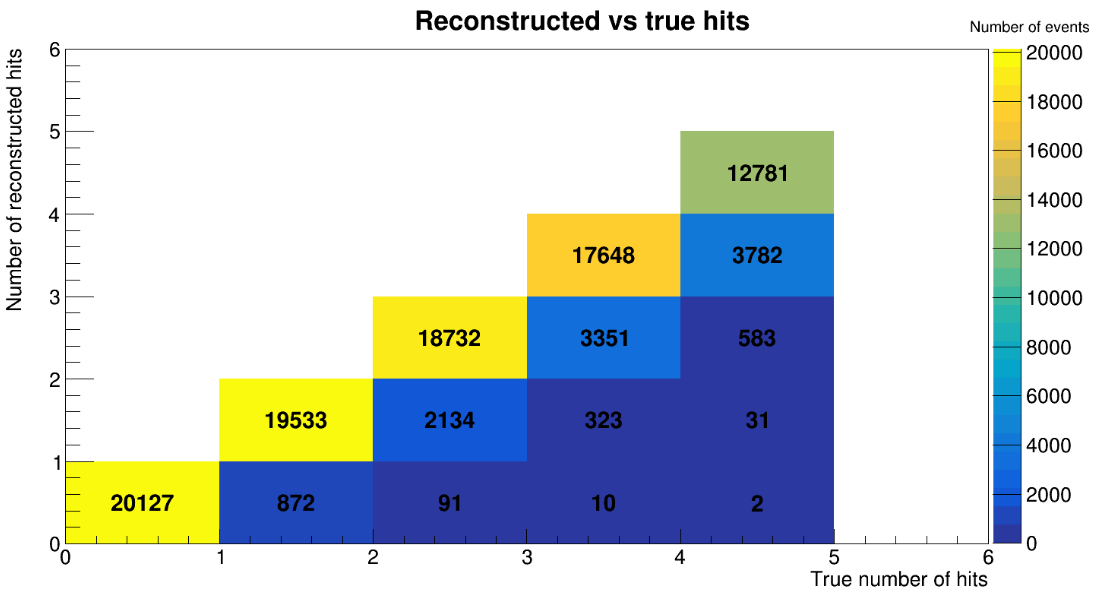
DNN pulses identification

- Labels (desired output) are vectors of the same length as the input data
  - 1024 samples; almost all values are zeroes
  - If a signals starts at t_i, the value of the label at t_i is the signal's amplitude
- CNN with the same structure as for the unsupervised learning
  - i.e. if it can filter the noise, it can recognize what a signal is :)
- Reconstruction program to scan and identify the signals both in the labels (i.e. the desired output) and the produced ML output – generator/network comparison

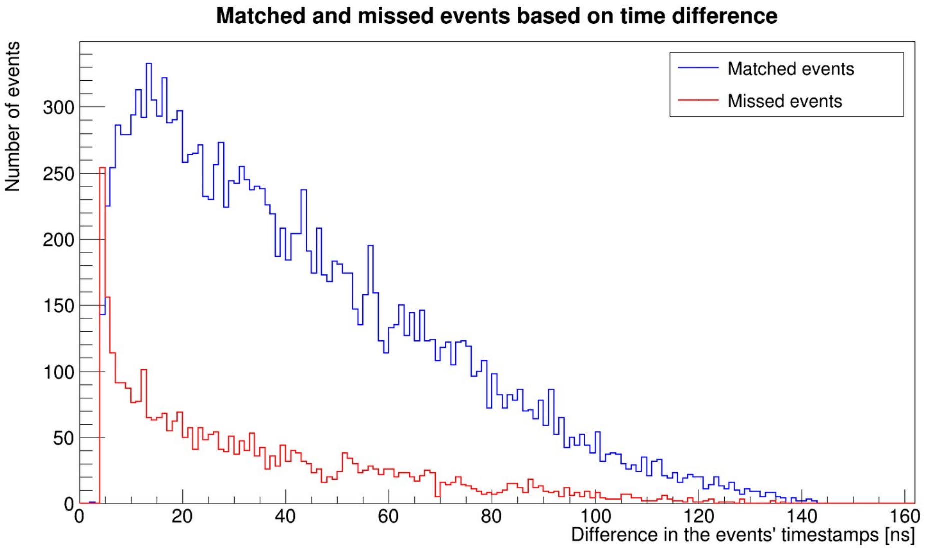


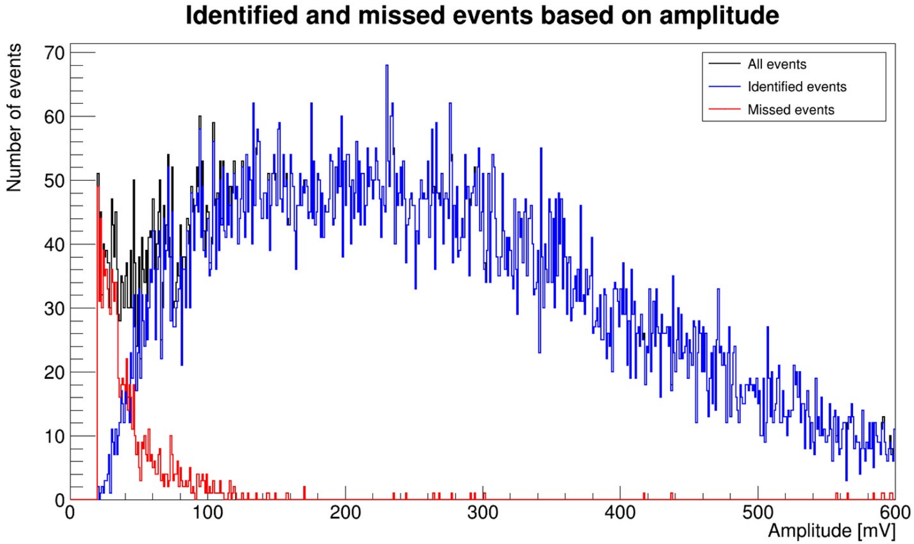


DNN performance

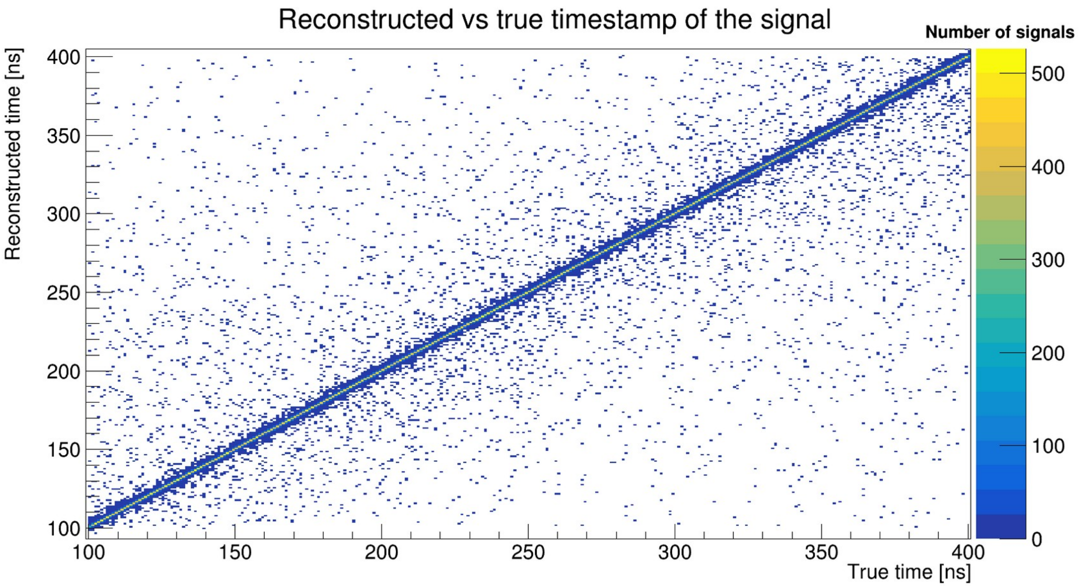


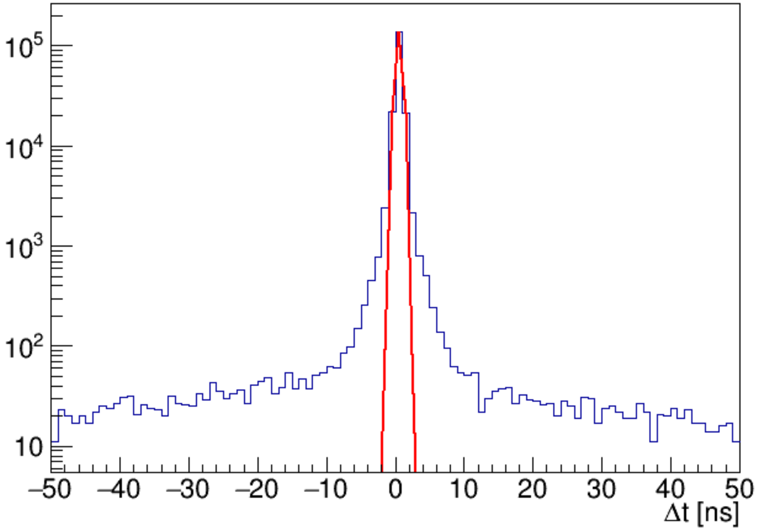
- Efficiency for lower numbers of signals are higher because of unrecognized signals from events with higher numbers
- For closely located signals: Most of the missed events are with dt < 10 ns
- Most of the events with amplitudes < 50mV are not identified





Time reconstruction

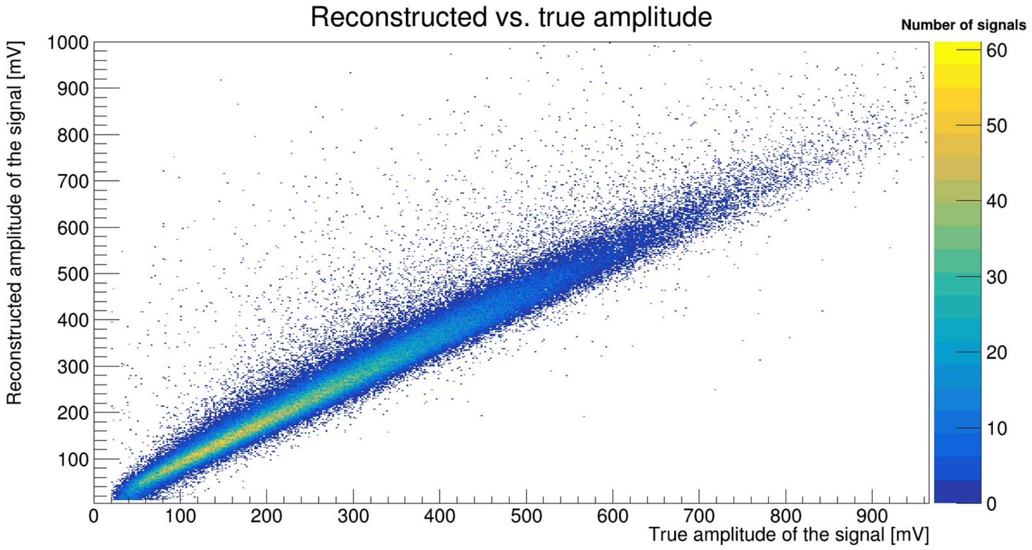


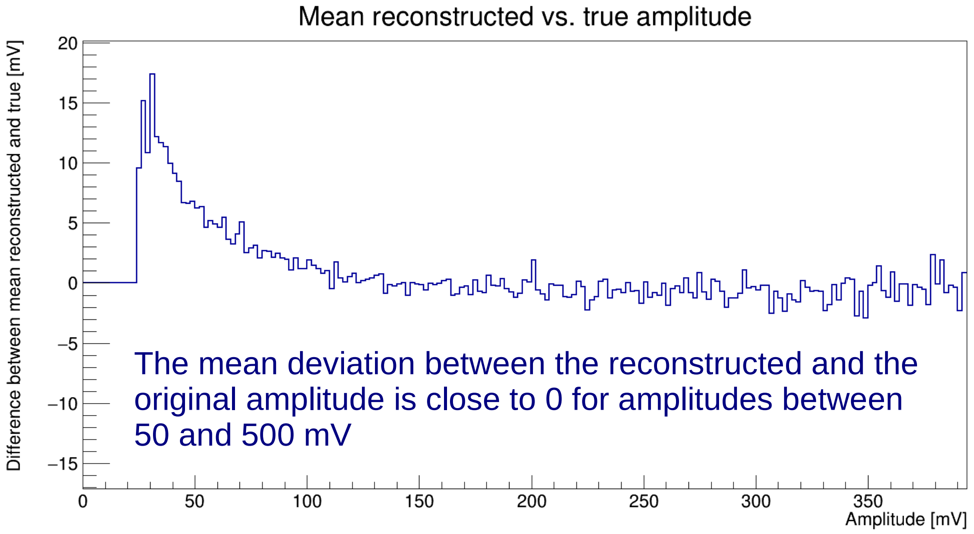


- Δt distribution is symmetric, non-gaussian tails exist
  - σ ~ 520 ps, RMS ~ 3.2 ns
- If the time of the true hit and the found hit is < 2 ns, we consider the identification successful

Amplitude reconstruction

- Strong correlation between real and reconstructed amplitude
  - The difference between them increases linearly
  - Single additional calibration constant is “sufficient” → energy scale
- Non-linear part for the small amplitudes

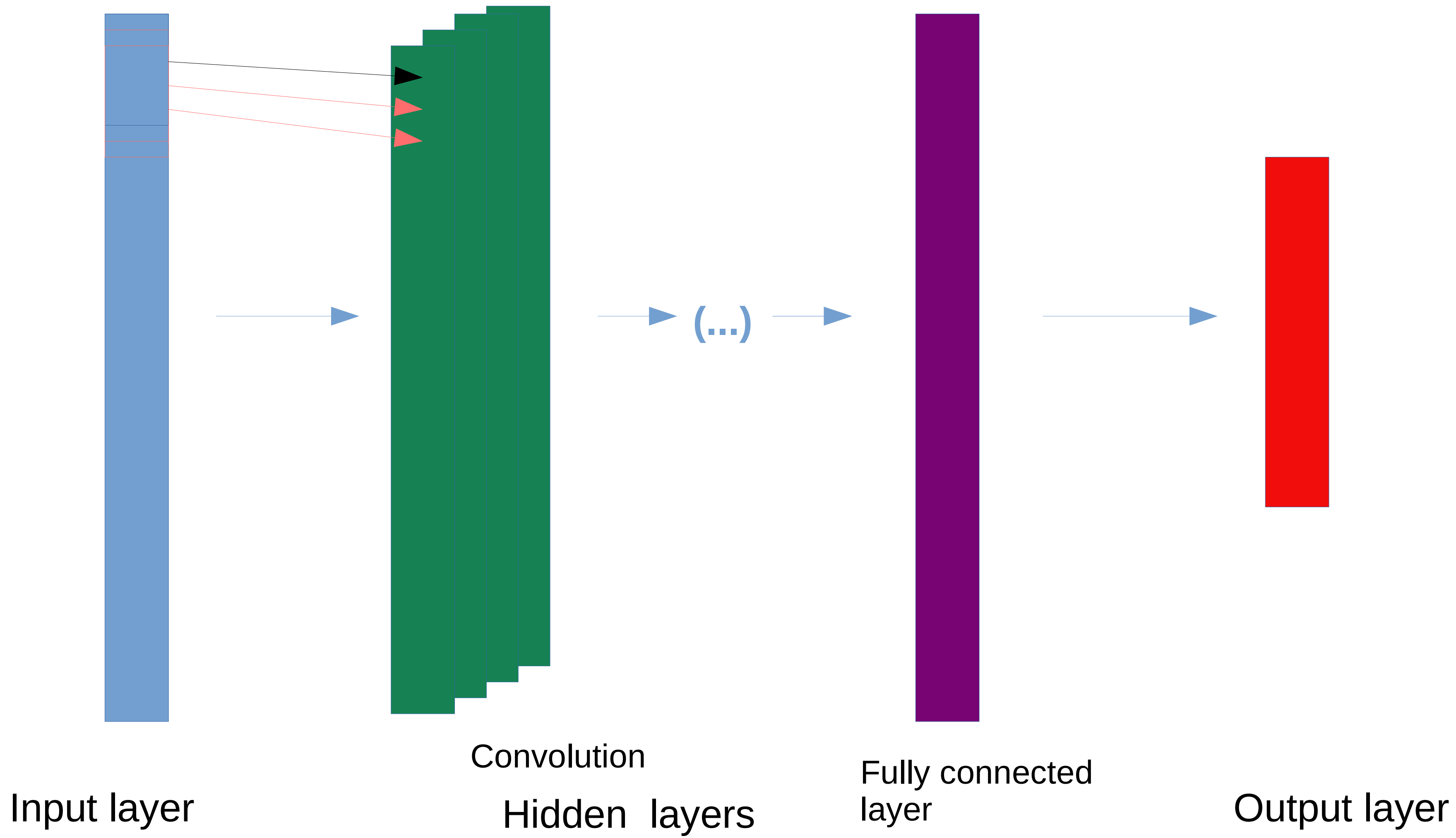




Conclusions

- PADME calorimetric system has to provide reliable energy reconstruction and shower separation
- Different ML topologies for signal reconstruction tested
  - Classification → number of signals
  - Unsupervised learning → noise filtration
  - Regression methods → signal parameters estimation
- AI performance assessed trough interpretability and explainability of the results
- Time resolution and amplitude reconstruction give promising results

1-Dimensional Convolutional Neural Networks



Supervised autoencoder

- Moving to supervised learning
- Labels (desired output) are vectors of the same length as the input data
  - 1024 samples
  - Almost all values are zeroes
  - If a signals starts at $\boldsymbol{t_i}$, the value of the label at $\boldsymbol{t_i}$ is the signal's amplitude
- CNN with the same structure as for the unsupervised learning
  - i.e. if it can filter the noise, it can recognize what a signal is :)

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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0 0 0 0 178 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 871 0 0 0 0 0 0 0 0 0 0
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