

## A D V A C A M Imaging the Unseen



# Machine learning models for single-particle classification with Timepix 3 detector

<u>Katerina Sykorova<sup>1</sup></u>, Lukas Marek<sup>1</sup>, Zdenek Buk<sup>2</sup>, Miroslav Cepek<sup>3</sup>, Jaroslav Solc<sup>4</sup>, Michal Andrlik<sup>5</sup>, Vladimir Vondracek<sup>5</sup>,Carlos Granja<sup>1</sup>, Cristina Oancea<sup>1</sup>

<sup>1</sup> ADVACAM s.r.o., Prague, Czech Republic
 <sup>2</sup> Department of Theoretical Computer Science, Czech Technical University, Prague, Czech Republic
 <sup>3</sup> Department of Applied Mathematics, Czech Technical University, Prague, Czech Republic

<sup>4</sup>Czech Metrology Institute, Brno, Czech Republic

<sup>5</sup> Proton Therapy Center Czech, Prague, Czech Republic

#### Introduction

Timepix 3 chips [1] have single particle detection sensitivity. Particle creates a signal spread over multiple pixels. These signals can be combined into a cluster.

#### AdvaPIX/MiniPIX Timepix 3

- Timepix 3 readout chip
- 256 x 256 pixels with 55 um pitch size





Different particle types produce clusters with different features. Particle classification is investigated for TraX Engine software [2].



- Measure deposited energy and time of arrival from every pixel
- Data-driven readout data sent out immediately after a pixel is hit, while the rest of the chip remains sensitive.

### Single-particle classification

Single particle clusters were classified into 5 distinct categories: **electrons + photons, alpha particles**, **ion nuclei** (except He), **low energy protons** (E < 100 MeV) and **high energy protons** (E > 100 MeV). Machine learning methods were employed to facilitate particle classification:

- Bidirectional Long Short-Term Memory recurrent Neural Network (BI-LSTM) [3]
- Fully connected Neural Network (NN) [4]
- Gradient boosted Decision Trees (Cat-Boost) [5]

Former method facilitates the time-ordered sequence of pixels in clusters, the latter two evaluate cluster features. Linear energy transfer (LET), energy distribution across the cluster and its thickness and linearity, have the greatest impact on the final classification. Models were trained on database of reference (calibration) data.

#### **Electron – photon classification**

We used the **Gaussian Mixture unsupervised machine learning** [6] technique to categorize electrons and photons into two classes effectively corresponding to:

- Class 0: Photons in the photo-effectdominant regime (below ~ 100 keV)
- Class 1: Electrons and photons in the Compton effect-dominant regime (above ~ 100 keV)



Radiation source	Energy [MeV]	Labeled Class 0	Labeled Class 1
<sup>90</sup> Sr	0.549; 2.3 (beta)	14.0 %	86.0 %
е	8.0	0.0 %	100.0 %
е	16	0.0 %	100.0 %
е	21	0.0 %	100.0 %
<sup>60</sup> Co	0.31 (beta) 1.17; 1.33 (gamma)	43.3 %	56.7 %
X-ray	0.033	99.7 %	0.3 %
X-ray	0.049	99.4 %	0.6 %
X-ray	0.083	97.3 %	2.7 %
X-ray	0.16	98.9 %	1.1 %
p, 0	deg	p, 88 deg	



#### Mixed radiation field from radiotherapeutic proton beam

A mixed radiation field was measured in a water phantom located behind the Bragg peak of a primary proton beam with an energy of 200 MeV at the Proton Therapy Center in Prague. The results were then compared with a Monte Carlo simulation.



#### **Proton directional analysis**

To analyze the direction of incoming protons, we used **Gradient Boosted Decision Trees**. Proton directions were classified into five categories (**0-15 deg**, **30 deg**, **45 deg**, **60 deg**, **75 deg**, **85-90 deg**) based on available training and testing reference data.



#### References

[1] T. Poikela *et al* 2014 *JINST* **9** C05013
[4] P. J. Werbos 1982 Springer **38**[2] L. Marek *et al* 2024 *JINST* **19** C04026
[5] L. Prokhorenkova *et al*. 2018 *NIPS* 31
[3] M. Schuster *et al* 1997 *IEEE* **45**, no. 11
[6] W. E. L Grimson *et al* 1999 252 **2**