# **Applications of Machine Learning** methods to Dark Matter search The CYGNO use-case

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Al@INFN - Artificial Intelligence at INFN





### CYGNO a large TPC for dark matter and neutrino study objective

exploiting the progress in commercial scientific Active Pixel Sensors (APS) based on CMOS technology to realise a large gaseous Time Projection Chamber (TPC) for **Dark Matter and Solar Neutrino search.** 





### **nuclear recoil threshold** why light mass gaseous based TPC?



#### gassous low (O 100 eV) threshold just some ideas to increa

just some ideas to increase sensitivity and scalability



## discrimination



solid/cryogenics

CREEST





# the dark matter when living on the earth

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Cygnus

#### galaxy rotation







A TCP is costituite by a vessel filled with gas or liquid (Ar, Xe, etc) where an appropriate field is applied (typically kV/cm)





when a charged particle pass true the gas, have a well known probability to ionise the gas and ...

Readout







Readout





... start to drift in the direction of the anode and the cathode where ...

Readout





Incident particle



Readout





in gas TCP an amplification process by means of triple **Gas Electron Multiplier** (GEM) and produce an avalanche of electrons ...





#### ... that generate photons with an efficiency ~ 7-8% in HeCF4 gas mixture.



## optical readout in a nutshell



an **sCMOS** camera 2304×2304 resolution, 0.7 electrons rms, equipped with standard optics collects the photons produced





## optical readout in a nutshell



**4 PMTs** symmetrically placed around the camera to detect the time shape longitudinal evolution



## optical readout in a nutshell



#### **PMTs**

Wavefor 0

cosmic and radioactivity at see level. in 500 ms image over 30\*30 cm area



2000



## underground signal and background







Dense Energy

### CYGNO (tech goal) to CYGNO 30 (physic goal) the bet



5\*10 litres, 1 camera 2.5 MB/event 0.2—>0.01 Hz



### CYGNO (tech goal) to CYGNO 30 (physic goal) the bet



5\*10 litres, 1 camera 2.5 MB/event 0.2—>0.01 Hz 1\*10^3 litres, 18 cameras 45 MB/event (Hz ?)





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1.3 GB/event (Hz ?)



### particle identification "gym" nuclear recoil, neutrino vs beta/gamma discrimination

- exploiting dE/dx ionisation power (density)
- exploiting dE/dx ionisation profile vs path (shape, head-tail, snaking, etc)
- exploiting directionality
- exploiting time shape profile

up to now we are **training our software** in the "**sea level**" gym" where natural radioactivity and cosmic rays are the main issue to deal with, generating strong occupancy and pileup in the data. This has forcing us to develop code aimed mainly at removing **background** (not expected underground) than to identify the signal

LIME, just installed underground, will allow to **test code** in the real environment and validate the Montecarlo simulation



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#### clustering unsupervised learning NCC, KNN, HC to DBSCAN



<sup>55</sup>Fe source, in 50 ms image over 30\*30 cm area

Elapsed time 10 events: 49.4



we start using NCC (Nearest Neighbors Clustering), K-Nearest Neighbors (KNN), Hierarchical clustering to arrive to Density Based Spatial Clustering able to detect closer in noise environments (DBSCAN)

DEBUG: number of points, clusters: 4865 255

['iTr: 0.00', 'cluster\_lable: 255.00', 'pixels: 310.00', 'photons: 2121.00', 'ph\_pixels: 6.84', 'x0start: 1148.00', 'y0start: 2160.00', 'x0end: 1148. 'y0end: 2176.00', 'width: 15.50', 'height: 34.87', 'pearson: –0.30']

> due to the interactions of photos of **5.9** keV, easily identifiable by cluster shape/ density very useful for detector energy calibration. This signal up to know have to be select among environmental and



#### **DBSCAN+K-means** <sup>55</sup>Fe source example detector resolution estimation









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### reconstruction flow chart intensity **DBSCAN**



noise filter: median filter optical correction: vignetting, optical distortion superclustering: Geodesic Active Contour (GAC)





### **iDDBSCAN** i-ntensity Directional DBSCAN to identify cosmic rays





3 - Nearby points are added to the cluster based on the fit.

4 - The fit is updated whenever new points are added to the cluster.





### Fully Convolutional Network for pixel-wise selection U-Net Fully Convolutional Network

- handle with the sensor noise is not trivial
- Gaussian thermal noise (exposure)
- tail due to **telegraph** noise (random discrete fluctuations or switching events as a function of time) typical of CMOS devices
- in the real life GEM discharge, FC discharge + physics

noise is simulated considering the PDF function of each pixels of the cameras tested



sample

sample



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## Fully Convolutional Network for pixel-wise selection U-Net Fully Convolutional Network

- objective: increase signal pixels sent to reconstruction code, decreasing the number of background pixels, reducing the number of processed elements
- noise simulated by considering the density probability function of each pixel on camera.
- signal simulated with GEANT4 (for ER) or SRIM (for NR) 1-60keV
- each pixel is classified as signal or background
- 70% of samples were using for training









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#### deep learning models comparison **Deep Neural Network, Random Forest Classifier, Gradient Boosted Classifier**

- **interaction** of the particles with gas is simulated using either GEANT4 (for ER) or SRIM (for NR)
- detector/readout effects are added to these track i.e. diffusion, camera noise, effective ionisation, gain fluctuations and geometrical acceptance etc.
- digitised images are reconstructed with a density based algorithm to find the cluster around the track.
- topological informations of reconstructed track can be used as discriminating variables (features)
- features: Length Along Principle Axis (LAPA), Maximum Density (MaxDen), Cylindrical Thickness (CylThick), Standard Deviation of Charge Distribution (SDCD), etc.
- the features were used for training the networks.

30 keV NR SRIM + digitalisation

30 keV ER **GEANT +** digitalisation



**GSSI.**ii et al. Lopez. Prajapati and Gustavo V.

#### deep learning models comparison Deep Neural Network, Random Forest Classifier, Gradient Boosted Classifier







ionisation, diffusion and propagation in HeCF<sub>4</sub>

measured sensor noise 10ms



Nuclear Recoil (NR) interaction and propagation simulated by SRIM (1-40keV)



GSSI.it 0 Prajapati and Gustavo V. Lopez. et al. 4

#### deep learning models compared Deep Neural Network, Random Forest Classifier, Gradient Boosted Classifier





#### DNN

- the weights of the network are optimised iteratively
- result is the output of the last layer
- It can build each tree independently
- results are combined at the end of the process



#### ER NR

RFC

#### GBC

- It builds one tree at a time
- It combines results along the way

**GSSI.**ii Gu Prajapati and

## model comparison





background: ER cla each ener

nuclear recoil detection efficiency 50% eff signal(0.075% bkg)-RFC 0.65 eff signal(0.045% bkg)-RFC 50% eff signal(0.45% bkg)-GBC 40% eff signal(0.27% bkg)-GBC 0.60 0.55 0.55 ignal(0.99% bkg)-DNN signal(0.45% bkg)-DNN 0.45 0.40 25 35 20 30 10 15 5 Energy [KeV]

Prelim

pround Bkg (50% eff signal-RFC) Bkg (40% eff signal-GBC) Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-BNN) Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Bkg (40% eff signal-DNN) Comparison Bkg (40% eff signal-DNN) Bkg (40% eff signa	models	NR det eff. [%]	background eff. [%]
	RFC	50	0.075
		40	0.045
	GBC	50	0.45
		40	0.27
	DNN	50	0.99
		40	0.45
	Traditional Approach	50	3.5
		40	0.8
	L		1

minimum NR efficiency in each energy bin is the signal efficiency and background (ER) efficiency is the overall background classified as signal in all energy bins. traditional approach: simple cut on the variable.



### next steps 1/2 **Convolutional Neural Network**

- operate on real data with CNN for the reconstruction, classification and computing physical quantities associated to the track.
- A ResNet model and a CNN classifier is already been made and tested on simulated data.

#### results of CNN are very similar to the one of DNN



ER classification 92.3% DNN ->91.6% CNN NR classification 95.9% DNN -> 97.6% CNN









#### next steps 2/2 **combining CMOS and PMTs data**



### infrastructure - schematic view **CLOUD INFN use-case**







### Conclusion actually a work in progress...

- be apply, tested and skills can grow up.
- more realistic data
- At the LNGS Laboratory the bet will be to look for sub millimetric tracks of NR operational energy and directional threshold

# our experiment is probably an ideal use-case where machine learning methods can

• up to now we have played with our code in a "gym" where the environment is very different from the one where the detector is now installed and is going to start taking

 this allow us to develop code able to deal with very hard background condition and trained us to start deal with unsupervised and supervise machine learning methods

respect to the most luckily **background** of the ER (beta/gamma) to find the ultimate



#### gas detector for DM & neutrino "ionisation" detectors





CYGNO/INITIUM



### LIME prototype design

overground/underground first phase:

- 50 cm drift made of Cu ring 33\*33 cm
- **50kV Cu** cathode (up to 1kV/cm)
- triple **GEM** stack amplification stage
- Iow radioactivity PMMA vessel
- 50 litres sensitive volume with an **He/CF4** based mixture at **atmospheric pressure**
- a single sCMOS Active Pixel Sensors (APS) HAMAMATSU camera + Schneider commercial **optics**
- 4 **PMT** symmetrically placed around the sensor for **time** shape
- Aluminum faraday cage







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### LIME prototype tracking performance



#### Example of a few cosmic tracks in LIME (Long Imaging ModulE)









### LIME prototype overground performance

- distribution of the **light content** of the <sup>55</sup>Fe events reconstructed from the sCMOS images (left), and distribution of the charge measured by the PMT signals (right).
- behaviour of the normalised number of <sup>55</sup>Fe spots as a function of the drift electric field (left) and event depth in the **sensitive volume** (right)
- dependence of  $\eta$  on the left and  $\eta$ PMT on the right as a function of the track distance from the GEM
- detection efficiency for nuclear recoils (Etotal) as a function of their detected energy for electron recoils efficiency of 4% (squares) and 1% (circles).



#### The CYGNO Experiment. Instruments 2022, 6, 6. https://doi.org/10.3390/instruments6010006

### LIME prototype beta/gamma performance/calibration







good linearity response in the energy range 4.5 keV - 45 keV

