Deep learning meets very-high-energy gamma-ray astronomy

Reconstructing events from imaging atmospheric Cherenkov telescopes with deep convolutional neural networks

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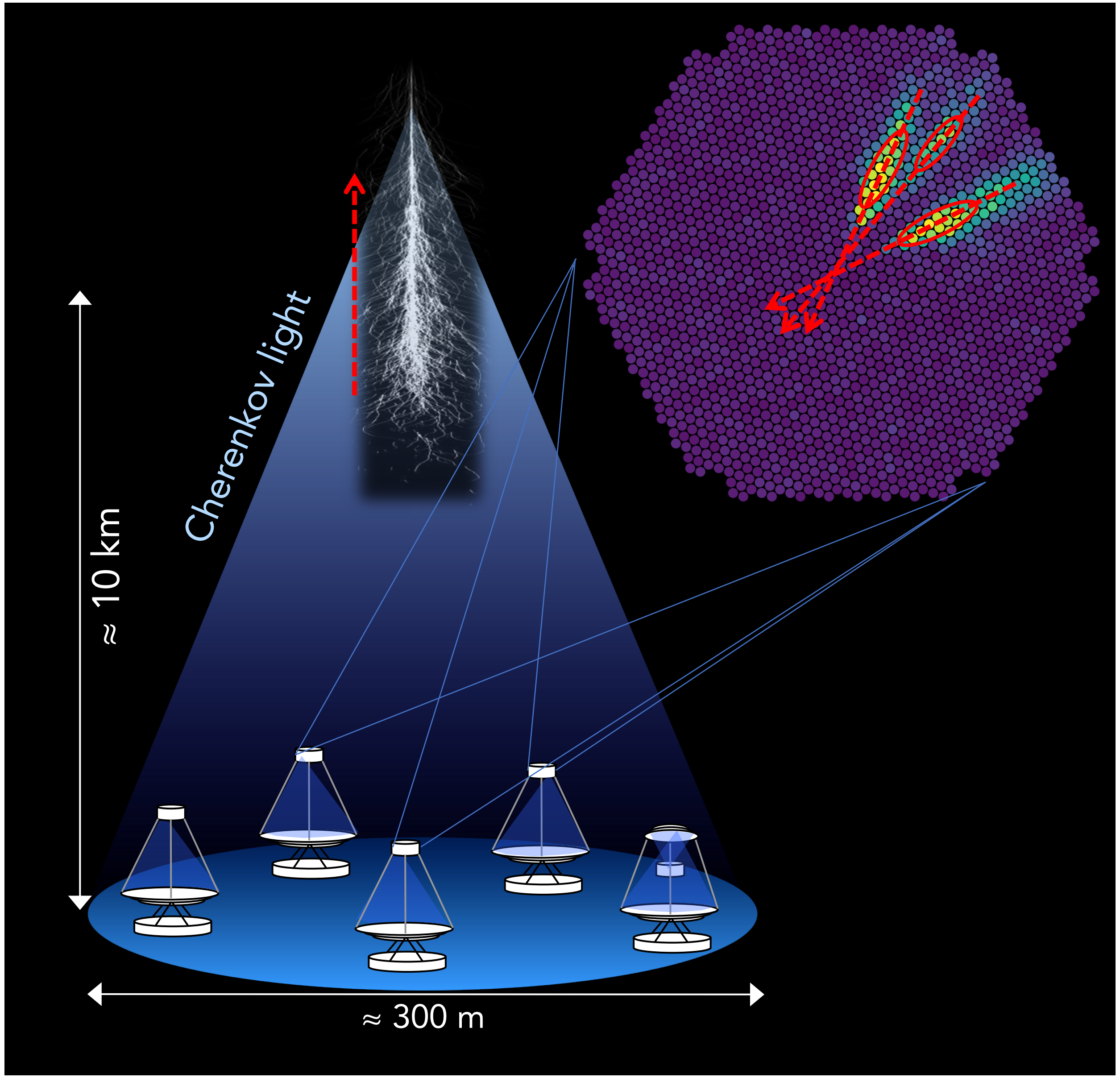
Abstract

Imaging atmospheric Cherenkov telescopes (IACTs) are excellent tools to inspect the very-high-energy (few tens of GeV and above) gamma-ray sky. This kind of telescope captures images of the air showers, originated by the absorption of gamma rays and cosmic rays by the atmosphere, through the detection of Cherenkov photons emitted in the shower. One of the main factors determining the sensitivity of IACTs to gamma-ray sources is how well reconstructed the properties of the primary particle triggering the air shower are: specifically, this particle reconstruction enables us to classify gamma-ray events from the much more frequent background of cosmic-ray events, and to infer the energy and arrival direction of the gamma-ray-like events. In this contribution we will discuss how deep convolutional neural networks (DCNs) are being explored as a promising method for IACT event reconstruction. We illustrate the discussion with some preliminary results from CTLearn: a Python package under development that includes modules for running deep learning models with TensorFlow, using pixel-wise camera data as input, for IACT event reconstruction.

Imaging atmospheric Cherenkov telescopes



- Detection of extended air showers using the atmosphere as a calorimeter
- Huge gamma–ray collection area (~10^5 m^2)
- Energy window: tens GeV - tens TeV
- Large background from charged CR
  - Partly irreducible (e^-/e^+, single-EM, with current methods)
- Event reconstruction from images:
  - Primary classification (gamma / CR)
  - Primary energy estimation
  - Primary arrival direction
- Current reconstruction methods:
  - Classical machine learning (Random Forest, Boosted Decision Trees) and look-up-tables
- **Event reconstruction directly affects IACT sensitivity to gamma-ray sources**

Deep learning for IACT event reconstruction: CTLearn

Core developers
DN, Tjark Miener (IPARCOS-UCM)
Ari Brill, Qi Feng (Columbia)
Bryan Kim (UCLA, now at Stanford)

- High-level Python package for using deep learning for IACT event reconstruction
- Configuration-file-based workflow and installation with conda drive reproducible training and prediction
- Supports any TensorFlow model that obeys a generic signature
- Open source on GitHub:
  https://github.com/ctlearn-project/ctlearn
  https://pos.sissa.it/358/752

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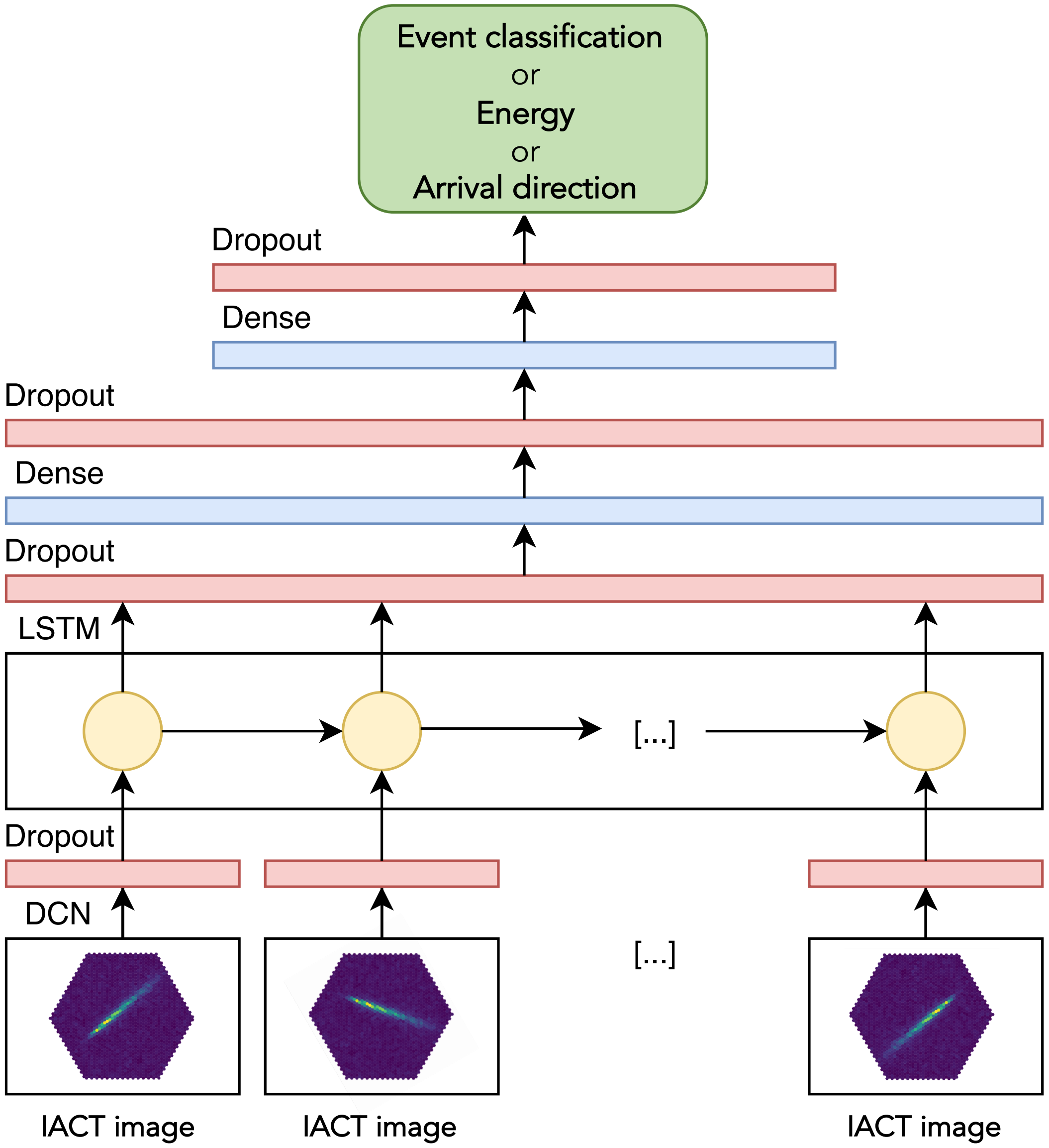


CTLearn: some results on event classification for CTA

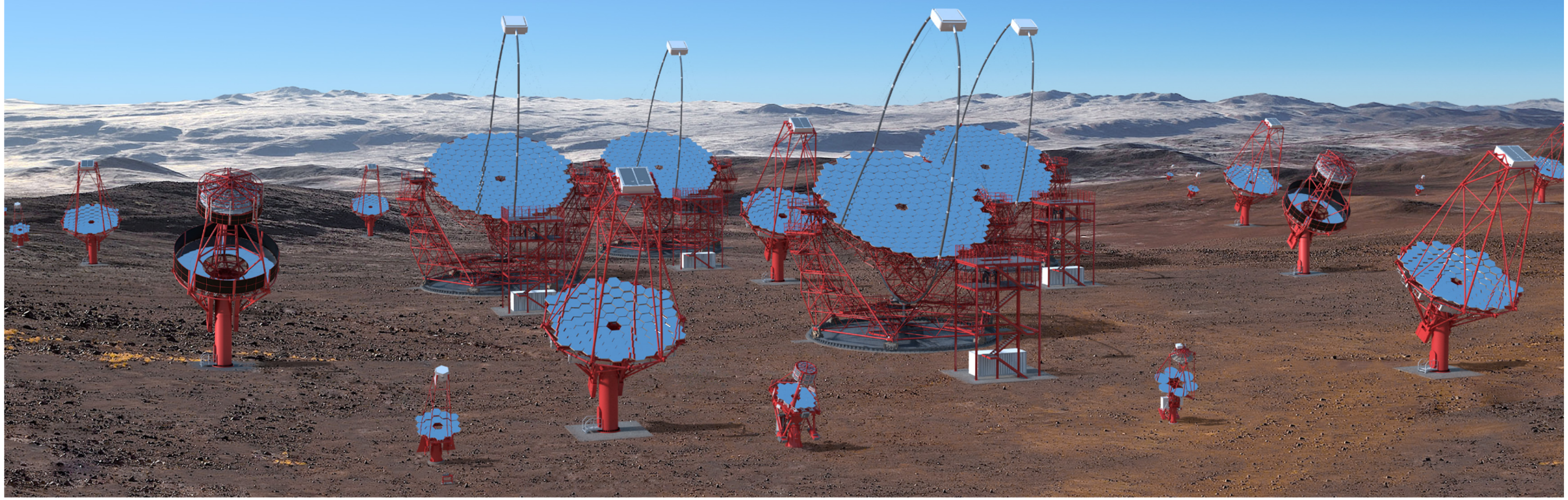
- 5-20 fold better sensitivity w.r.t. current IACTs
- 4 decades of energy coverage: 20 GeV to 300 TeV
- Improved angular and energy resolution
- Two arrays (North/South)

cta cherenkov telescope array — the observatory for ground-based gamma-ray astronomy

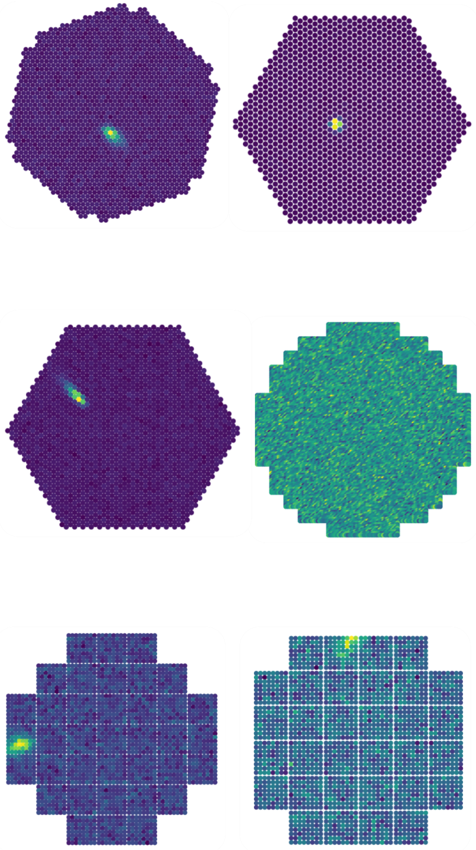
Low-energy range:
23 m ø
Parabolic reflector
4° - 5° FoV
Energy threshold 20 GeV

Mid energy-range:
12 m ø modified Davies-Cotton reflector
9.7 m ø Schwarzschild-Couder reflector
7° - 8° FoV
Best sensitivity in the 100 GeV – 10 TeV range

High-energy range:
4 m ø Davies-Cotton reflector
4 m ø Schwarzschild-Couder reflector
9 - 10° FoV
Several km^2 area at multi-TeV energies



Networks trained on labeled, simulated data

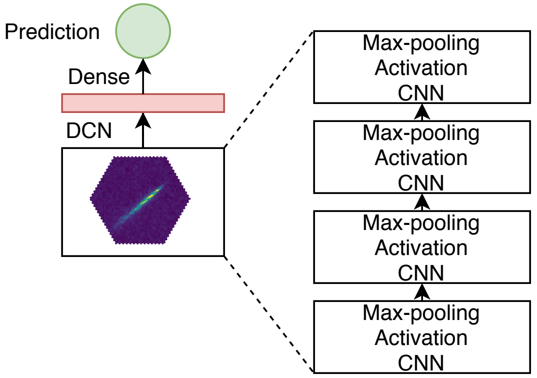


www.cta-observatory.org/

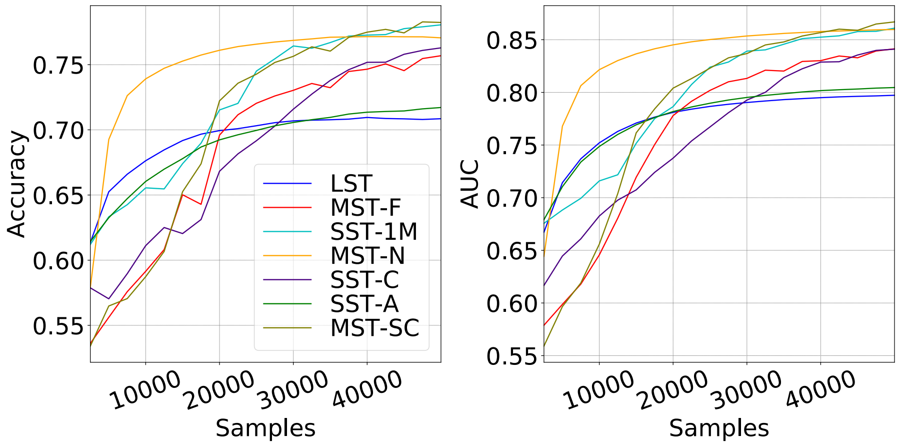
Science with CTA, arXiv:1709.07997

Camera images courtesy of T. Vuillaume

CTLearn: some results on event classification for CTA



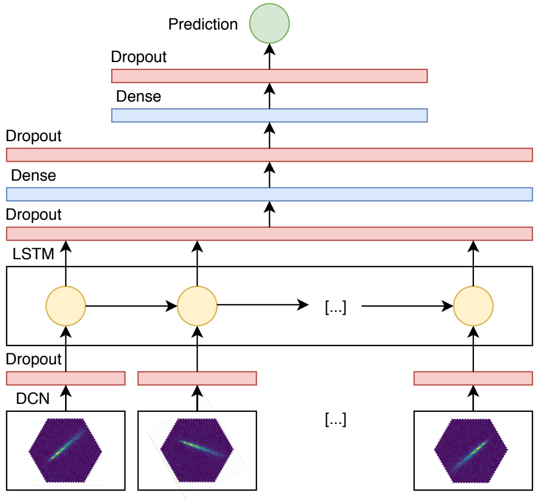
Single-tel model



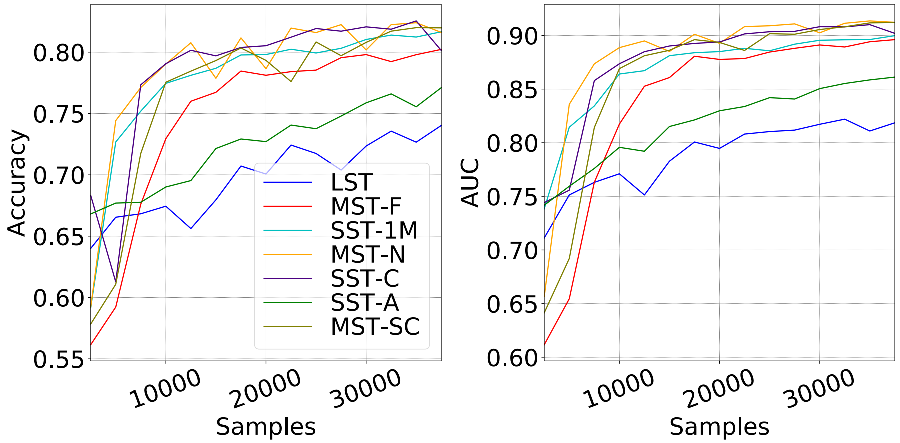
Training metrics for the *single-tel* model

Single-tel model		LST	MST-F	MST-N	MST-SC	SST-1M	SST-C	SST-A
Validation	Acc	0.701	0.762	0.784	0.795	0.781	0.753	0.733
	AUC	0.786	0.849	0.869	0.878	0.862	0.828	0.818
Test	Acc	0.697	0.757	0.778	0.785	0.776	0.748	0.725
	AUC	0.778	0.842	0.863	0.866	0.853	0.822	0.808
CNN-RNN model		LST	MST-F	MST-N	MST-SC	SST-1M	SST-C	SST-A
Validation	Acc	0.740	0.802	0.816	0.820	0.817	0.801	0.771
	AUC	0.819	0.896	0.912	0.912	0.900	0.902	0.861
Test	Acc	0.732	0.800	0.816	0.812	0.809	0.796	0.771
	AUC	0.815	0.890	0.909	0.902	0.893	0.898	0.862

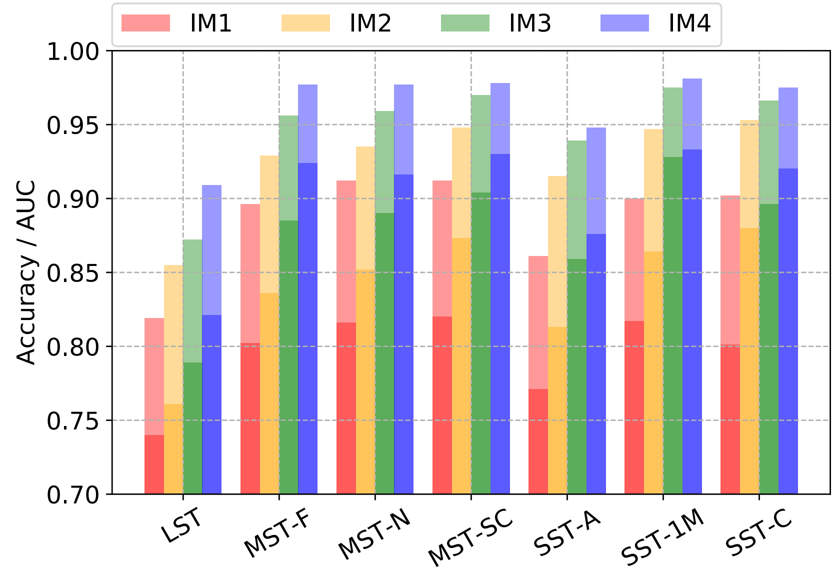
Results for the *single-tel* and *CNN-RNN* models



CNN-RNN model



Training metrics for the *CNN-RNN* model

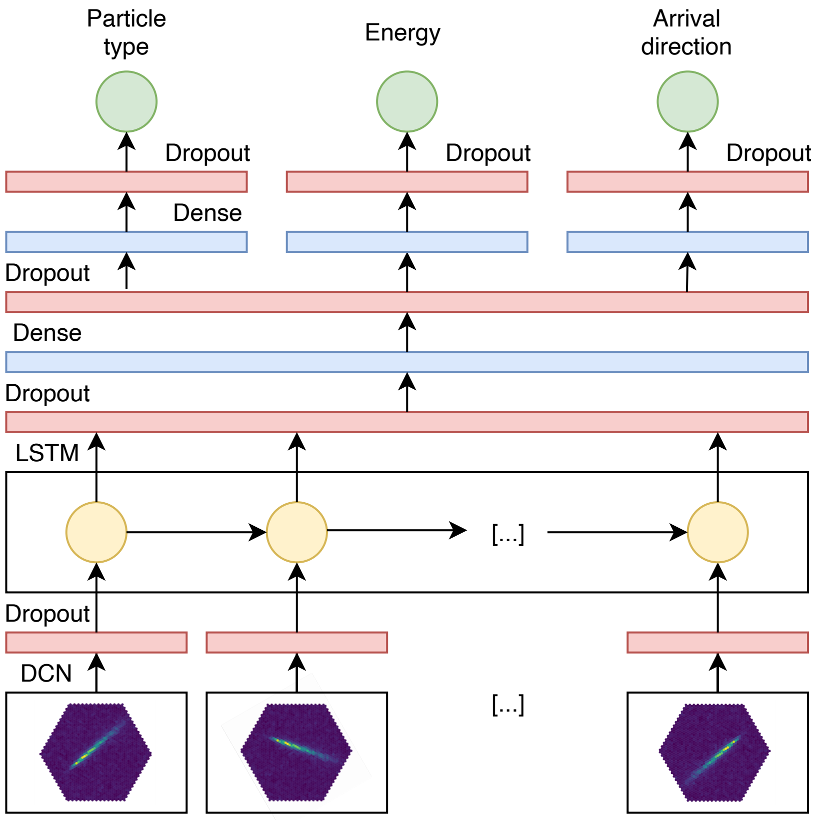


Effect of image multiplicity cut for the *CNN-RNN* model

Outlook

- Current-generation IACTs have enhanced their performances through ML
- Next-generation IACTs may profit from latest developments in ML

- Ongoing efforts to exploit deep learning as an event reconstruction method for IACTs
  - Event classification over non-parametrized images demonstrated!
  - Working on:
    - optimizing architectures
    - multi-task learning
    - support for current-generation IACTs (MAGIC, VERITAS, H.E.S.S.)



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