The performance of the MAGIC telescopes using deep convolutional neural networks with CTLearn

DOI 10.5281/zenodo.4576196

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Abstract

The Major Atmospheric Gamma Imaging Cherenkov (MAGIC) telescope system is located on the Canary Island of La Palma and inspects the very high-energy (VHE, few tens of GeV and above) gamma-ray sky. MAGIC consists of two imaging atmospheric Cherenkov telescopes (IACTs), which capture images of the air showers originating from the absorption of gamma rays and cosmic rays by the atmosphere, through the detection of Cherenkov photons emitted in the shower. The sensitivity of IACTs to gamma-ray sources is mainly determined by the ability to reconstruct the properties (type, energy, and arrival direction) of the primary particle generating the air shower. The state-of-the-art IACT pipeline for shower reconstruction is based on the parameterization of the shower images by extracting geometric and stereoscopic features and machine learning algorithms like random forest or boosted decision trees. In this contribution, we explore deep convolutional neural networks applied directly to the pixelized images of the camera as a promising method for IACT full-event reconstruction and present the performance of the method on observational data using *CTLearn*, a package for IACT event reconstruction that exploits deep learning.

Introduction

In this contribution, we show how deep convolutional neural networks (CNNs) can be utilized to detect astrophysical gamma-ray sources like the Crab Nebula using *CTLearn*[a], a deep learning framework for IACT event reconstruction, and *DL1-Data-Handler*[b], a package designed for the data management of machine learning image analysis techniques for IACT data.

Validation on MC simulations

For this work, we selected *CTLearn*'s Thin-ResNet (TRN) model, which is a shallow residual neural network with 34 layers. We explore stereoscopic information by concatenating the images (integrated pixel charges and signal arrival times) of the two MAGIC telescopes channel-wise before feeding the network. The images are calibrated and cleaned by the MAGIC Analysis and Reconstruction Software *MARS* to suppress the major fraction of the Night Sky Background (NSB). To evaluate the performance common metrics like ROC curves, energy and angular resolution curves are used, applying the same quality cuts.

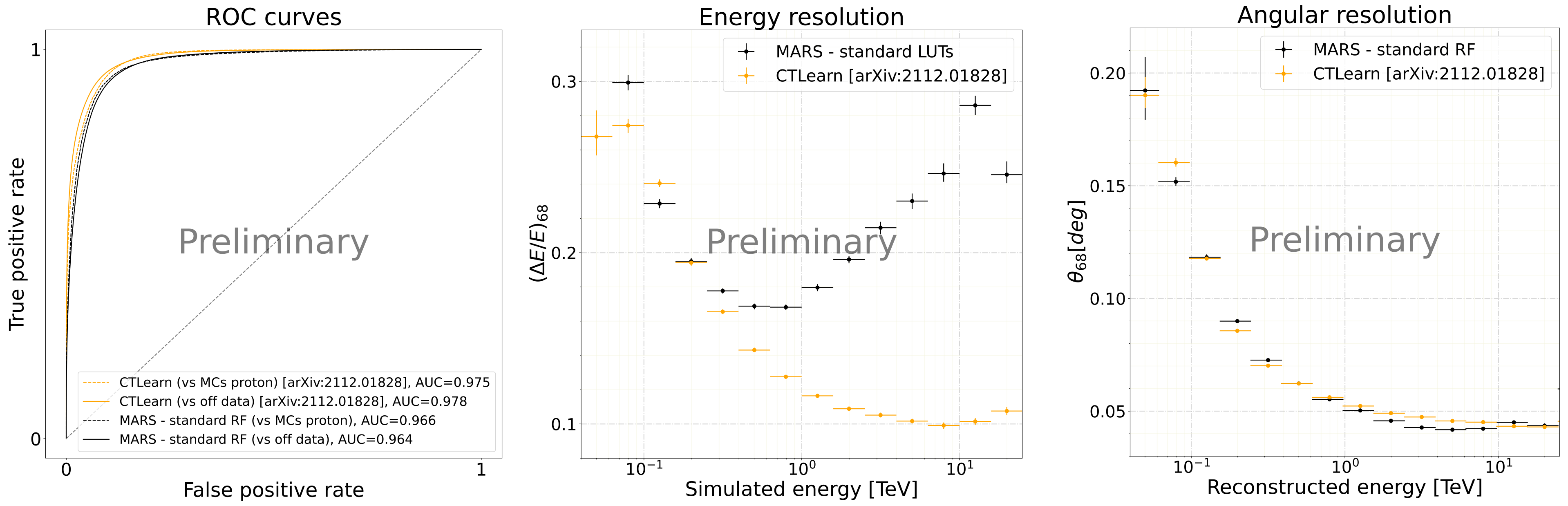


Fig. 1: Reconstruction performance of CTLearn on MC simulations of the MAGIC telescopes [1].

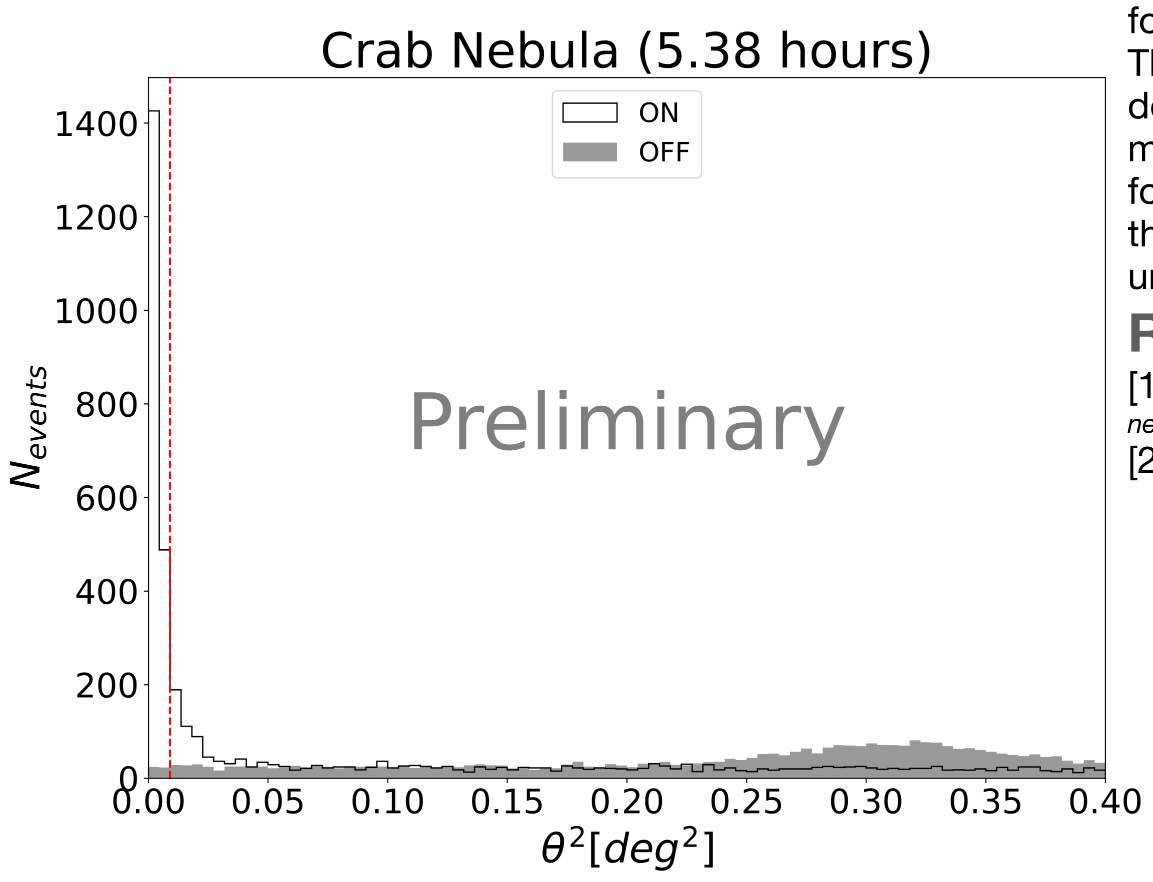
Results on observational data

We analyzed 5.38 h of observations on the standard gamma-ray candle the Crab Nebula, taken with the MAGIC telescopes on four different nights in 2016 under good weather condition at low zenith distance (zd < 35°). We used *MARS* and *CTLearn* with two settings focusing on the medium energy (ME; E > 250 GeV) and low energy (LE; E > 100 GeV) range. For a fair comparison between the different analysis methods, the background (bkg) rates of the *CTLearn* analyses are adjusted to match for the corresponding standard *MARS* analyses (ME or LE). The Crab Nebula is detected using θ^2 plots (see Fig. 2 for the *CTLearn* ME analysis), where θ is the angular separation of the source position and the reconstructed arrival direction of the high-energy photon. The main results of all analyses are summarized in Tab.1. The significance is calculated following Li&Ma [2]. The sensitivity is computed as the strength of the source that gives excess/sqrt(background) = 5 after 50h with the condition of excess/background > 5% and is given in percentage of the Crab Nebula flux.

Analysis	N_{on}	N_{off}	N_{ex}	Gamma rate [/ min]	Bkg rate [/ min]	Sensitivity [% Crab]	Significance (Li&Ma)
MARS - Medium energy	1934	45.3±3.9	1888.7±44.1	5.85±0.14	0.140±0.012	0.58±0.03	66.6
CTLearn - Medium energy	1907	46.0±3.9	1861.0±43.8	5.77±0.14	0.143±0.012	0.60±0.03	66.0
MARS - Low energy	7933	1827.3±24.7	6105.7±92.4	18.91±0.29	5.661±0.076	1.50±0.01	83.7
CTLearn - Low energy	7889	1826.3±24.7	6062.7±92.2	18.78±0.29	5.658±0.076	1.51±0.01	83.2

Tab. 1: Summary of all performed analyses (LE/ME and *MARS*/*CTLearn*) of the same Crab Nebula sample.

Fig. 2: θ² plot for the CTLearn ME analysis.



Conclusion

This contribution shows that CNN-based full-event reconstruction works for MC simulations and observational data of the MAGIC telescopes. The performance obtained with *CTLearn* matches the sensitivity of detection of the conventional analysis on real data. The selected TRN model is relatively shallow and further performance enhancements are foreseen by increasing the model depth/complexity. We plan to evaluate the full performance of the MAGIC telescopes with CNN-based analysis under various observation conditions in the future.

References

[1] T. Miener et al., *IACT event analysis with the MAGIC telescopes using deep convolutional neural networks with CTLearn* [arXiv:2112.01828]

[2] T. P. Li and Y. Q. Ma , *Analysis methods for results in gamma-ray astronomy.* [doi:10.1086/161295]

Acknowledgements

We would like to thank the Instituto de Astrofísica de Canarias for the excellent working conditions at the Observatorio del Roque de los Muchachos in La Palma. The financial support of the German BMBF, MPG and HGF; the Italian INFN and INAF; the Swiss National Fund SNF; the ERDF under the Spanish Ministerio de Ciencia e Innovación (MICINN) (FPA2017-87859-P, FPA2017- 85668-P, FPA2017-82729-C6-5-R, FPA2017-90566-REDC, PID2019-104114RB-C31, PID2019-104114RB-C32, PID2019- 105510GB-C31C42, PID2019-107847RB-C44, PID2019-107988GB-C22); the Indian Department of Atomic Energy; the Japanese ICRR, the University of Tokyo, JSPS, and MEXT; the Bulgarian Ministry of Education and Science, National RI Roadmap Project DO1-268/16.12.2019 and the Academy of Finland grant nr. 317637 and 320045 are gratefully acknowledged. This work was also supported by the Spanish Centro de Excelencia "Severo Ochoa" SEV-2016- 0588, SEV-2017-0709 and CEX2019-000920-S, and "María de Maeztu" CEX2019-000918-M, the Unidad de Excelencia "María de Maeztu" MDM-2015-0509-18-2 and the "la Caixa" Foundation (fellowship LCF/BQ/PI18/11630012), by the Croatian Science Foundation (HrZZ) Project IP-2016-06-9782 and the University of Rijeka Project 13.12.1.3.02, by the DFG Collaborative Research Centers SFB823/C4 and SFB876/C3, the Polish National Research Centre grant UMO-2016/22/M/ST9/00382 and by the Brazilian MCTIC, CNPq and FAPERJ.
TM acknowledges support from PID2019-104114RB-C32. JLC and DN acknowledges partial support from The European Science Cluster of Astronomy & Particle Physics ESFRI Research Infrastructures funded by the European Union's Horizon 2020 research and innovation program under Grant Agreement no. 824064. We acknowledge the support of NVIDIA Corporation with the donation of a Titan X Pascal GPU used for part of this research.

[a] https://github.com/ctlearn-project/ctlearn [b] https://github.com/cta-observatory/dl1-data-handler www.magic.iac.es