Generation of Air Shower Images for Imaging Air Cherenkov Telescopes using Diffusion Models

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Abstract

For the analysis of Imaging Air Cherenkov Telescopes (IACTs) data, numerous air shower simulations are needed to derive the instrument's response. A process that is both computationally intensive and often requires repetition under varying observation conditions. Generative models based on deep neural networks offer an ultra-fast and more efficient alternative, significantly accelerating simulation times while compactly storing vast simulation libraries. Previous works focused on the generation of gamma showers; however, mostly proton showers need to be simulated for a good background description that features larger fluctuations, making their generation significantly more challenging. In this study, we employ diffusion models to generate proton showers for an IACT with nearly 2,000 pixels. Using simulations from the H.E.S.S. experiment, we assess the quality of the generated images via low-level observables and established shower shape parameters. While the generated images demonstrate high-quality low-level properties, further refinement is needed in modeling distinct shower shapes.

*Work partly performed at Lawrence Berkeley National Laboratory.

Machine Learning and the Physical Sciences Workshop, NeurIPS 2024.

1 Introduction

Over the past two decades, arrays of Imaging Air Cherenkov Telescopes (IACTs), like the High Energy Stereoscopic System (H.E.S.S.) [1] changed our understanding of the very-high-energy (VHE) gamma-ray sky. These telescopes image Cherenkov radiation emitted from secondary particles in extensive air showers induced by cosmic particles. The IACT images are then analyzed to extract information about the primary particle [2].

Accurate gamma-ray measurements require extensive Monte Carlo (MC) simulations [3, 4] to thoroughly understand instrument performance, particularly for the hadronic background, outnumber gamma rays by 1 to $10^3 - 10^4$. Running millions of events for different observation conditions is time-consuming and memory-inefficient. Recent advances in machine learning, particularly generative models, provide new methods for tackling the challenges of acceleration and refining [5, 6] of high-dimensional simulation data [7–9]. In particle physics, Generative Adversarial Networks (GANs)[10–13], normalizing flows[14, 15], and diffusion models [16–20] have been used to accelerate simulations significantly with minimal loss of accuracy. To meet the computational demands of upcoming observatories like the Cherenkov Telescope Array (CTA)[21], recent studies have explored the efficient generation of IACT parameters and images using GANs[22–25]. Initial results are promising [26], but generating high-resolution IACT images with comprehensive fidelity for hadronic showers remains challenging.

Inspired by the application to calorimeters [19, 27], we use score-based diffusion models [28] in this work to generate proton IACT air shower images, using simulations from the H.E.S.S. CT5 telescope with its FlashCam design [29]. Since stereoscopic integration is an ongoing challenge in deep learning [30–34], we focus on single-telescope images.

2 Diffusion models for the generation of IACT images

Diffusion generative models have shown state-of-the-art quality in image synthesis and promising performance as fast surrogate models for expensive physics simulations. In particular, diffusion models used to reproduce the detector response of calorimeters in collider experiments such as CaloScore [19, 27] have shown improved fidelity compared to previous machine learning approaches. Diffusion models are trained by adding a time-dependent perturbation to the data $\mathbf{x}$ such that:

$$\mathbf{x_t} = \alpha(t)\mathbf{x} + \sigma(t)\epsilon, \tag{1}$$

where $\epsilon \sim \mathcal{N}(0, 1)$. The role of the network $\mathbf{v}_\theta$ with trainable parameters θ is to perform an indirect denoising of the data by minimizing the loss:

$$\mathcal{L} = \mathbb{E}_{\mathbf{x}_t, t} \left\| \mathbf{v}_t - \mathbf{v}_\theta(\mathbf{x}_t, t) \right\|^2, \tag{2}$$

with time parameter $t \sim \mathcal{U}(0, 1)$ and velocity parameter $\mathbf{v}_t$ defined as $\mathbf{v}_t \equiv \alpha_t \epsilon - \sigma_t \mathbf{x}$. A cosine schedule is used for the perturbation parameters with $\alpha_t = \cos(0.5\pi t)$ and $\sigma_t = \sin(0.5\pi t)$, satisfying $\alpha^2 + \sigma^2 = 1$ for all time values. Sampling is then performed using the DDIM [35] sampler with X time steps.

A U-Net [36] model with attention layers [37] in the lower dimensions is used as the backbone network for the diffusion process on the pixel data. As observed in CaloScore, we can improve the generation quality by breaking down the model into two components. The pixel model learns to generate normalized images, where the sum of all pixels is set to unit for all input images. A second model based on the ResNet [38] architecture is then used to learn the overall normalization, improving the description of the energy deposition. Additional features, such as the impact parameters, are also included in the second model to improve the angular description of the incoming showers to be simulated. In this strategy, we first sample the overall normalization and impact parameters and use this information to condition the generation of the images.

Our diffusion model was trained for 500 epochs on eight A100 GPUs, which took about 9 hours. We used roughly 430 k images for training and validation with an 80:20 split. For the generation of new images, the energies of the test data sets are input to the diffusion model. This generated a set of 76 k IACT images in about 3 hours. In the following section, these generated images are compared to the test data images.

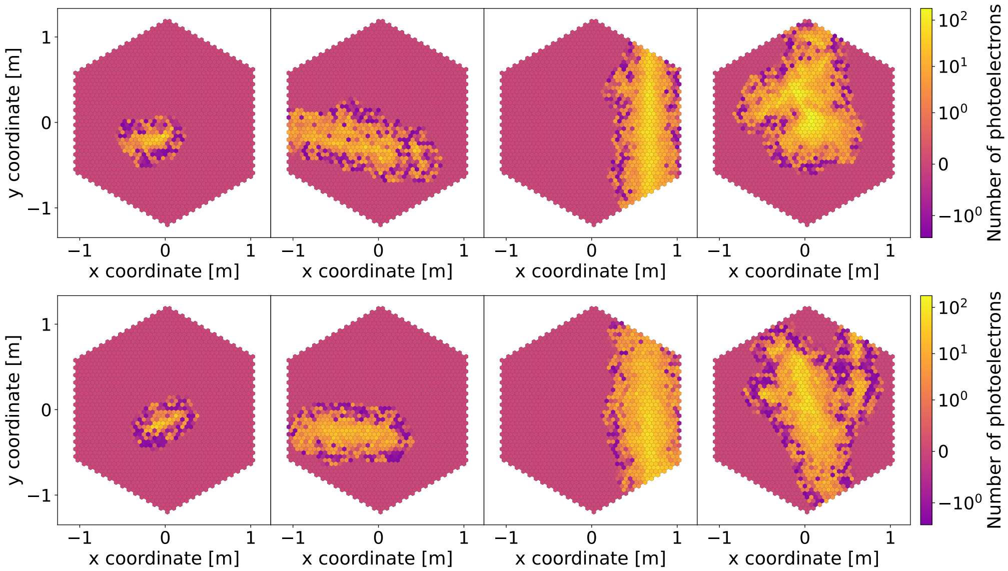

Figure 1: Comparison of four IACT images from the simulated test data set (top) and the generated data set (bottom). The simulated images are hand-picked to show various air shower characteristics while the four generated images are the next neighbors (in MSE).

3 Analysis of generated IACT images

After the IACT images are generated, the normalization is reverted and a post-processing function is applied. This function includes the removal of low-value noise, clipping of high pixel values, and the removal of low-signal images that do not fulfill the cut of 250 photoelectrons (p.e.). Both the simulated test data set and the generated data set contain about 76 k images each. To demonstrate that the generated images are similar to the simulated images, we study several aspects of the images. The generated images are inspected regarding their visual quality by qualitatively comparing typical air shower characteristics. After that, various parameters describing the images are investigated using high and low-level data. The analysis is carried out using the open-source tool ctapipe [39] (v0.21.2 [40]).

We show four images from the simulated test data set and the generated data set in figure 1. The simulated images are handpicked to show the various air shower characteristics that can appear in IACT proton images. Using the smallest pixel-wise difference in MSE, generated images are picked that are similar to the chosen simulated images. The images in the first two columns show elliptical signals that are almost completely detected by the camera. In the third column, the structures of the signals are more noisy and they are also highly truncated. The last two images show an example of a signal covering almost the whole camera. This comparison shows that the typical air shower characteristics can also be found in the images generated with the diffusion model.

Investigation of various image parameters After looking into the visual quality of the generated images, various image parameters characterizing the properties of the images need to be studied. In the following, four different parameters are analyzed, two low-level and two high-level parameters. The low-level parameters, also in this work referred to as pixel parameters, are the image size — the integrated signal of an image — and the pixel values. The high-level parameters are obtained from the so-called Hillas parameterization [2], which is a commonly used analysis procedure of IACT images in gamma-ray astronomy. The basic idea of this method is to parameterize the typically elliptical Cherenkov signal on the image, using the pixel locations and their signals. These parameters are used to analyze photon images, but they can also be used for the analysis of proton images with their more chaotic signals. Usually, the so-called tail-cut cleaning [41] — a two-threshold filtering algorithm — is applied to the IACT images to remove night sky background light, which does not belong to the Cherenkov signal. Furthermore, after the cleaning, another image size cut of 250 p.e. is applied to filter out low-signal images.

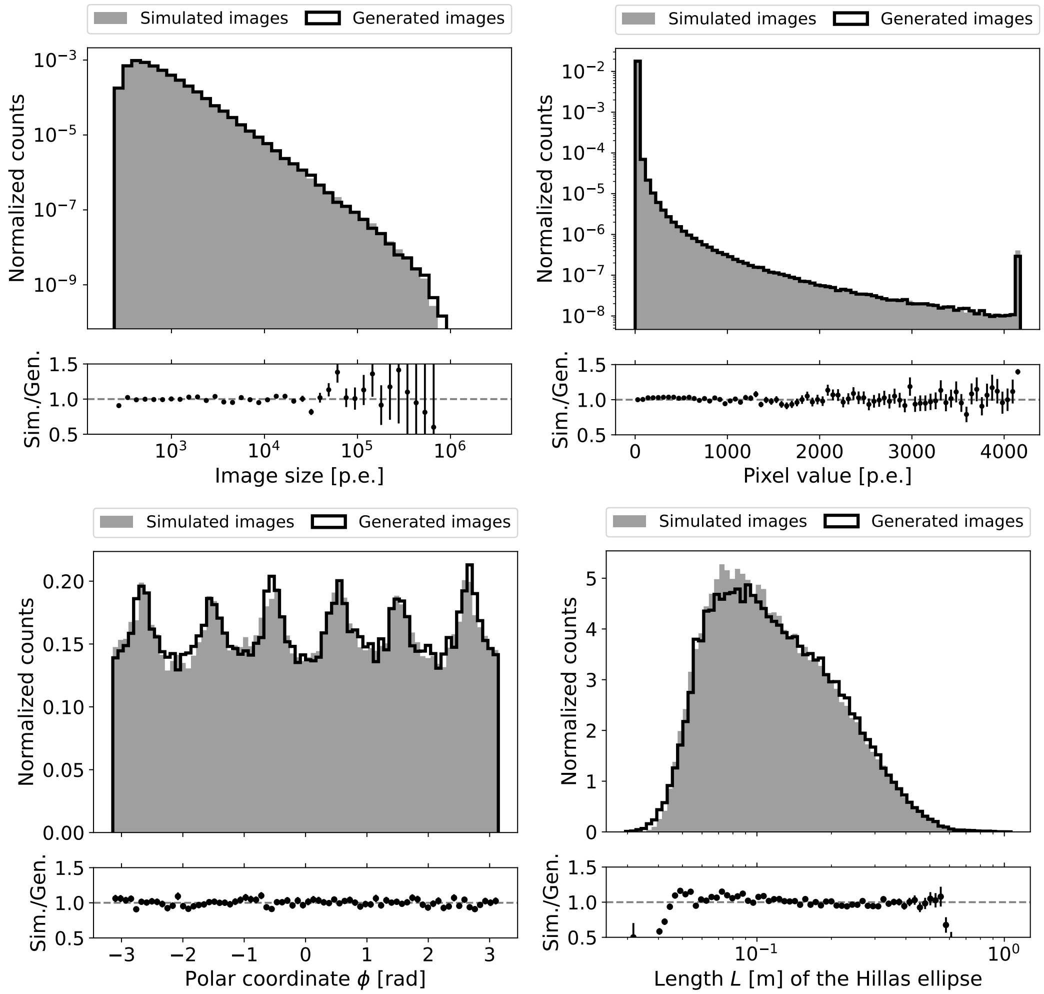

Figure 2: Distributions of two low-level parameters: the image size and the pixel values (top) and two high-level parameters: the polar coordinate and Hillas length (bottom) for the simulated test data set (gray) and the generated data set (black).

The pixel parameters, which are shown at the top of figure 2, are investigated, as they give direct information about the predictions of the diffusion model. For the image sizes, which are obtained from the second model, the distributions for both data sets match generally very well with some minor differences present at the highest and lowest values. From the main model, the pixel values are obtained using the image size from above and the air shower impact point as input. The values range from about -3 p.e. to 4176 p.e., with the higher value being the saturation value of the used photomultiplier tubes (PMTs). Overall, this shows that the diffusion model can learn the low-level features of the IACT images.

Out of all the possible Hillas parameters, the distributions of two of them are shown at the bottom of figure 2. The polar coordinate gives information about the location of the signal on the image and it is evident that the distributions for the simulated test data set and the generated data set match quite well. Even though the distribution contains six peaks, which correspond to the corners of the camera, the model shows no problem in learning this feature. However, the distributions of the other parameter — the Hillas length, which is the length of the major axis of the elliptical signal — show minor differences when comparing both data sets. This implies that the generation of an accurate signal shape is still moderately difficult for the model. So, while the diffusion model is already able to implement the physical shower characteristics on a high level into the images, it is still challenging for it to learn and generate all features correctly. Since the Hillas parameters play a key role in the analysis of IACT images, it is necessary to carry out more studies to improve the generated Hillas parameter quality and, thus, the quality of the generated images themselves.

4 Summary

We employed diffusion models in this work to generate air-shower images taken by IACTs. Our approach used simulations of the CT5 telescope at H.E.S.S., featuring a modern camera design with close to 2000 pixels, developed for CTA. Our method integrates the traditionally separated simulation of the air shower and the instrument response into a seamless end-to-end approach. In contrast to previous work that focused on gamma-ray showers, we investigated the generation of proton images that feature larger fluctuations and are more challenging to model. By utilizing score-based diffusion models, we generated the first images of proton showers using deep generative models.

The generated images are of promising quality. The studied low-level parameters showed good agreement with simulations. A high-level evaluation of the signal shapes using the Hillas parameters showed promising prospects. Whereas some shape variables are described well, the tail of distinct shape variables, like the Hillas length, are not well modeled, and more research is needed to yield models able to generate images of the whole phase space.

A current limitation of this work is the generation time. In comparison to image generation using GANs [26], the used approach requires ($\approx 10^4$) larger generation times and shows speedups in the order of 10 in comparison to the simulation. Future work will focus on accelerating the generation times of diffusion models [42–44].

References

[1] F. Aharonian et al. Observations of the crab nebula with HESS. *A&A*, 457(3):899–915, sep 2006. doi: 10.1051/0004-6361:20065351.

[2] A. M. Hillas. Cerenkov light images of EAS produced by primary gamma. In *19th Intern. Cosmic Ray Conf-Vol. 3*, number OG-9.5-3, 1985.

[3] D. Heck, J. Knapp, J. Capdevielle, G. Schatz, and T. Thouw. CORSIKA: A Monte Carlo code to simulate extensive air showers. 1998. doi: 10.5445/IR/270043064.

[4] K. Bernlöhr. Simulation of imaging atmospheric cherenkov telescopes with CORSIKA and sim_telarray. *Astropart. Phys.*, 30(3):149–158, October 2008. doi: 10.1016/j.astropartphys.2008.07.009.

[5] Martin Erdmann, Lukas Geiger, Jonas Glombitza, and David Schmidt. Generating and refining particle detector simulations using the Wasserstein distance in adversarial networks. *Comput. Softw. Big Sci.*, 2(1): 4, 2018. doi: 10.1007/s41781-018-0008-x.

[6] Yaxing Wang, Chenshen Wu, Luis Herranz, Joost van de Weijer, Abel Gonzalez-Garcia, and Bogdan Raducanu. Transferring gans: generating images from limited data. 2018.

[7] Matthew Feickert and Benjamin Nachman. A Living Review of Machine Learning for Particle Physics. 2 2021.

[8] Dan Guest, Kyle Cranmer, and Daniel Whiteson. Deep learning and its application to lhc physics. *Annual Review of Nuclear and Particle Science*, 68(1):161–181, October 2018. ISSN 1545-4134. doi: 10.1146/annurev-nucl-101917-021019. URL `http://dx.doi.org/10.1146/annurev-nucl-101917-021019`.

[9] M. Erdmann, J. Glombitza, G. Kasieczka, and U. Klemradt. *Deep Learning for Physics Research*. WORLD SCIENTIFIC, 2021. ISBN 978-981-12-3745-4. doi: 10.1142/12294.

[10] Luke de Oliveira, Michela Paganini, and Benjamin Nachman. Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis. *Comput. Softw. Big Sci.*, 1(1):4, 2017. doi: 10.1007/s41781-017-0004-6.

[11] Michela Paganini, Luke de Oliveira, and Benjamin Nachman. Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multilayer Calorimeters. *Phys. Rev. Lett.*, 120(4):042003, 2018. doi: 10.1103/PhysRevLett.120.042003.

[12] Michela Paganini, Luke de Oliveira, and Benjamin Nachman. CaloGAN : Simulating 3D high energy particle showers in multilayer electromagnetic calorimeters with generative adversarial networks. *Phys. Rev. D*, 97(1):014021, 2018. doi: 10.1103/PhysRevD.97.014021.

[13] Martin Erdmann, Jonas Glombitza, and Thorben Quast. Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network. *Comput. Softw. Big Sci.*, 3(1):4, 2019. doi: 10.1007/s41781-018-0019-7.

[14] Claudius Krause and David Shih. CaloFlow: Fast and Accurate Generation of Calorimeter Showers with Normalizing Flows. 6 2021.

[15] Claudius Krause and David Shih. Fast and accurate simulations of calorimeter showers with normalizing flows. *Phys. Rev. D*, 107(11), jun 2023. doi: 10.1103/physrevd.107.113003. URL `https://doi.org/10.1103%2Fphysrevd.107.113003`.

[16] Erik Buhmann et al. Caloclouds: Fast geometry-independent highly-granular calorimeter simulation. 2023.

[17] Fernando Torales Acosta, Vinicius Mikuni, Benjamin Nachman, Miguel Arratia, Kenneth Barish, Bishnu Karki, Ryan Milton, Piyush Karande, and Aaron Angerami. Comparison of Point Cloud and Image-based Models for Calorimeter Fast Simulation. 7 2023.

[18] Vinicius Mikuni, Benjamin Nachman, and Mariel Pettee. Fast Point Cloud Generation with Diffusion Models in High Energy Physics. 4 2023.

[19] Vinicius Mikuni and Benjamin Nachman. Score-based generative models for calorimeter shower simulation. *Phys. Rev. D*, 106(9):092009, 2022. doi: 10.1103/PhysRevD.106.092009.

[20] Matthew Leigh, Debajyoti Sengupta, Guillaume Quétant, John Andrew Raine, Knut Zoch, and Tobias Golling. PC-JeDi: Diffusion for Particle Cloud Generation in High Energy Physics. 3 2023.

[21] B. S. Acharya et al. Introducing the CTA concept. *Astropart. Phys.*, 43:3–18, 2013. ISSN 0927-6505. doi: https://doi.org/10.1016/j.astropartphys.2013.01.007. Seeing the High-Energy Universe with the Cherenkov Telescope Array - The Science Explored with the CTA.

[22] J. Dubenskaya, A. Kryukov and A. Demichev. Fast simulation of gamma/proton event images for the TAIGA-IACT experiment using generative adversarial networks. In *37th International Cosmic Ray Conference*, volume 395, page 874. SISSA Medialab, 2021. doi: 10.22323/1.395.0874.

[23] J. Dubenskaya et al. Using a Conditional Generative Adversarial Network to Control the Statistical Characteristics of Generated Images for IACT Data Analysis. In *Proceedings of The 6th International Workshop on Deep Learning in Computational Physics*. Sissa Medialab, nov 2022. doi: 10.22323/1.429.0004. URL `https://doi.org/10.22323%2F1.429.0004`.

[24] K.D. Hoang and D.A. Williams. Generating airshower images for the veritas telescopes with conditional generative adversarial network. In *38th International Cosmic Ray Conference*, volume 444, page 806. SISSA Medialab, 2023. doi: 10.22323/1.444.0806.

[25] Deivid Ribeiro, Yuping Zheng, Ramanakumar Sankar, and Kameswara Mantha. Optimizing the Wasserstein GAN for TeV Gamma Ray Detection with VERITAS. In *Proceedings of 38th International Cosmic Ray Conference — PoS(ICRC2023)*, volume 444, page 660, 2023. doi: 10.22323/1.444.0660.

[26] Christian Elflein, Stefan Funk, and Jonas Glombitza. Ultra-fast generation of air shower images for imaging air cherenkov telescopes using generative adversarial networks. *Journal of Instrumentation*, 19(04):P04010, April 2024. ISSN 1748-0221. doi: 10.1088/1748-0221/19/04/p04010. URL `http://dx.doi.org/10.1088/1748-0221/19/04/P04010`.

[27] Vinicius Mikuni and Benjamin Nachman. Score-based generative models for calorimeter shower simulation. *Physical Review D*, 106(9), November 2022. ISSN 2470-0029. doi: 10.1103/physrevd.106.092009. URL `http://dx.doi.org/10.1103/PhysRevD.106.092009`.

[28] Yang Song, Jascha Sohl-Dickstein, Diederik P. Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole. Score-based generative modeling through stochastic differential equations. *ArXiv*, 2021.

[29] Gerd Pühlhofer, Konrad Bernlöhr, Baiyang Bi, German Hermann, Jim Hinton, Ira Jung-Richardt, Fabian Leuschner, Vincent Marandon, Alison Mitchell, Lars Mohrmann, Daniel Parsons, Simon Sailer, Heiko Salzmann, Simon Steinmassl, Felix Werner, and for the H. E. S. S. collaboration. Science verification of the new FlashCam-based camera in the 28m telescope of H.E.S.S. 2021.

[30] I. Shilon et al. Application of deep learning methods to analysis of imaging atmospheric cherenkov telescopes data. *Astropart. Phys.*, 105:44–53, feb 2019. doi: 10.1016/j.astropartphys.2018.10.003.

[31] A. Brill et al. Investigating a deep learning method to analyze images from multiple gamma-ray telescopes. In *2019 New York Scientific Data Summit (NYSDS)*. IEEE, jun 2019. doi: 10.1109/nysds.2019.8909697.

[32] M. Jacquemont et al. First full-event reconstruction from imaging atmospheric cherenkov telescope real data with deep learning. In *2021 International Conference on Content-Based Multimedia Indexing (CBMI)*. IEEE, jun 2021. doi: 10.1109/cbmi50038.2021.9461918.

[33] S. Spencer et al. Deep learning with photosensor timing information as a background rejection method for the cherenkov telescope array. *Astropart. Phys.*, 129:102579, may 2021. doi: 10.1016/j.astropartphys.2021.102579.

[34] J. Glombitza, V. Joshi, B. Bruno, and S. Funk. Application of graph networks to background rejection in imaging air cherenkov telescopes. *JCAP*, 2023(11):008, November 2023. ISSN 1475-7516. doi: 10.1088/1475-7516/2023/11/008. URL `http://dx.doi.org/10.1088/1475-7516/2023/11/008`.

[35] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. *CoRR*, abs/2010.02502, 2020. URL `https://arxiv.org/abs/2010.02502`.

[36] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[37] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. 2023.

[38] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[39] Maximilian Linhoff, Lukas Beiske, Noah Biederbeck, Stefan Fröse, Karl Kosack, and Lukas Nickel. ctapipe – prototype open event reconstruction pipeline for the cherenkov telescope array. In *Proceedings, 38th International Cosmic Ray Conference*, volume 444, 2023. doi: 10.22323/1.444.0703.

[40] Karl Kosack, Maximilian Linhoff, Jason Watson, Jean Jacquemier, Lukas Nickel, Noah Biederbeck, Lukas Beiske, Tomas Bylund, Georg Schwefer, Alison Mitchell, Jonas Hackfeld, Michele Peresano, Christoph Deil, Anno Knierim, Stefan Fröse, Rune Michael Dominik, Samuel Timothy Spencer, Franca Cassol, Clara Escañuela Nieves, Thomas Vuillaume, Kai Brügge, Felix Werner, Satoshi Fukami, Michele Mastropietro, Jérémie Decock, Wrijupan Bhattacharyya, Abelardo Moralejo, francesco visconti, and Jose Enrique Ruiz. cta-observatory/ctapipe: v0.21.2 – 2024-06-27, June 2024. URL `https://doi.org/10.5281/zenodo.12571953`.

[41] Denys Malyshev and Lars Mohrmann. *Analysis Methods for Gamma-Ray Astronomy*, page 1–53. Springer Nature Singapore, September 2023. ISBN 9789811645440. doi: 10.1007/978-981-16-4544-0_177-1. URL `http://dx.doi.org/10.1007/978-981-16-4544-0_177-1`.

[42] Tim Salimans and Jonathan Ho. Progressive distillation for fast sampling of diffusion models. In *International Conference on Learning Representations*, 2022. URL `https://openreview.net/forum?id=TIdIXIpzhoI`.

[43] Zhaoyang Lyu, Xudong Xu, Ceyuan Yang, Dahua Lin, and Bo Dai. Accelerating diffusion models via early stop of the diffusion process. 2022.

[44] Qinsheng Zhang and Yongxin Chen. Fast sampling of diffusion models with exponential integrator. 2022.