Deep learning techniques for Imaging Air Cherenkov Telescopes

arXiv: 2206.05296

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Particle Physics on the Plains
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Outline

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- Brief Overview of Cosmic Ray

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- Detectors and their search strategies

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- Convolutional Neural Network and Autoencoder
- Methodology and Result

Cosmic Ray Flux

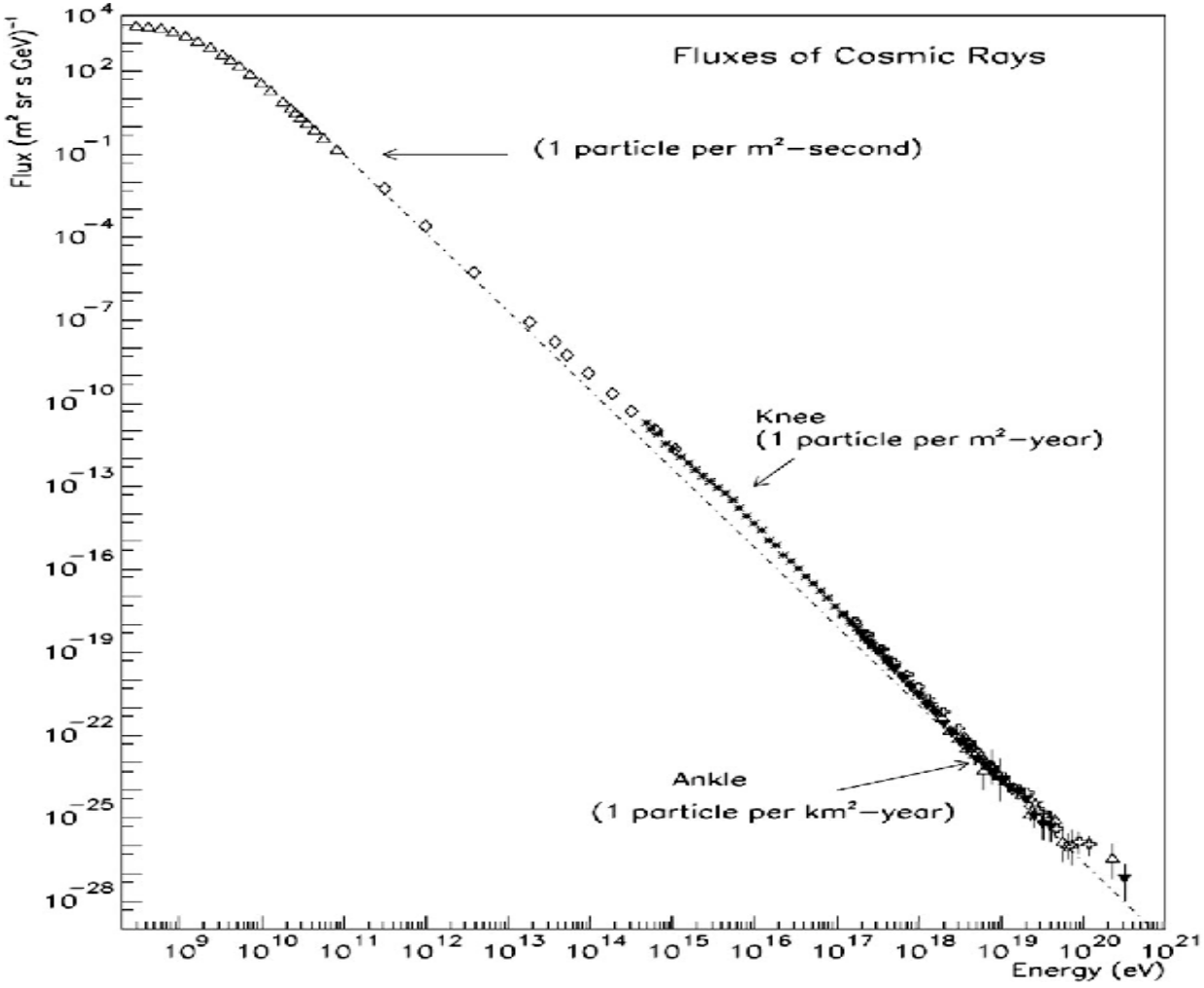

Figure: Cosmic ray flux as a function of energy [a]

[a] MALCOLM S. LONGAIR. High Energy Astrophysics. Cambridge University Press, 2011

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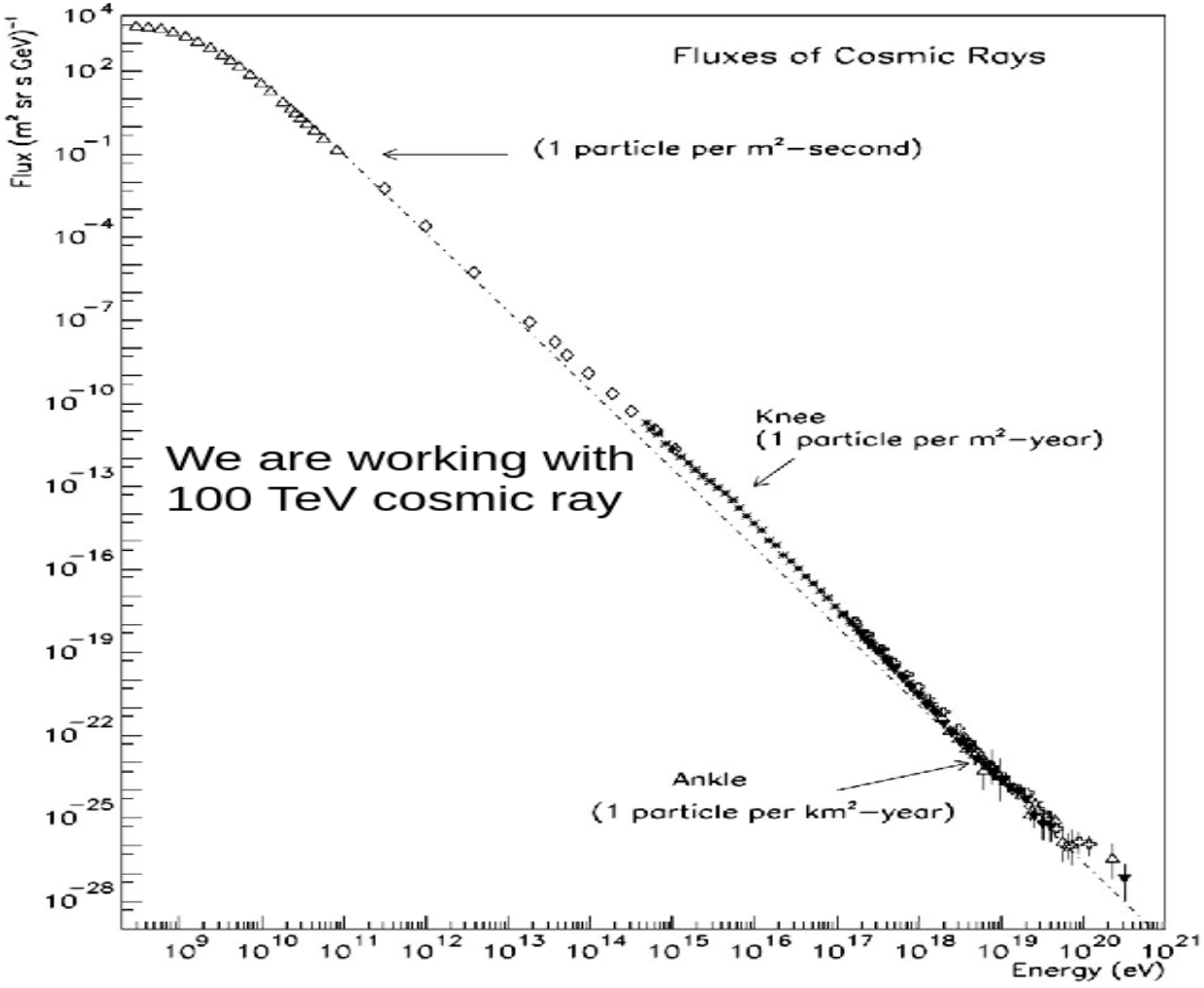

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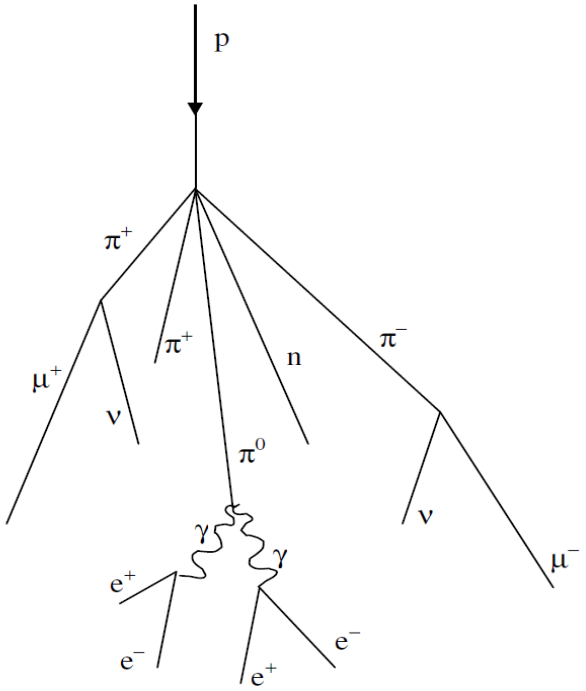
Detectors and their search strategies



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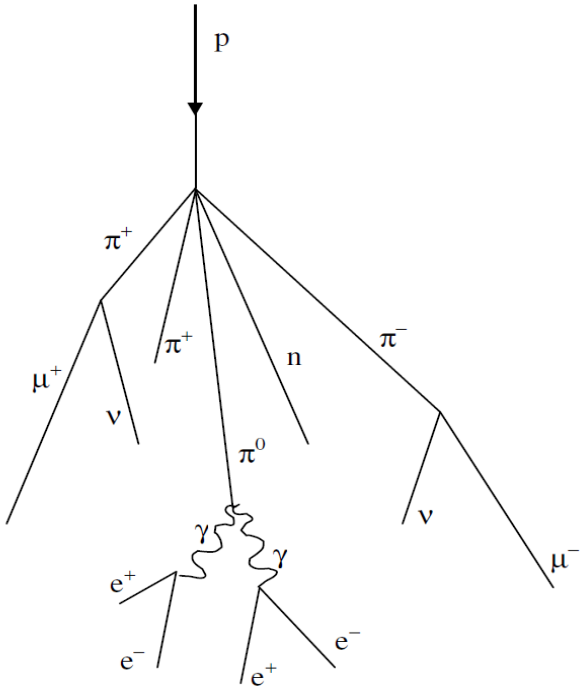

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- Cherenkov detectors:
  The current generation of IACT used in the experiments - MAGIC and VERITAS in northern hemisphere and HESS and CANGAROO in southern hemisphere.

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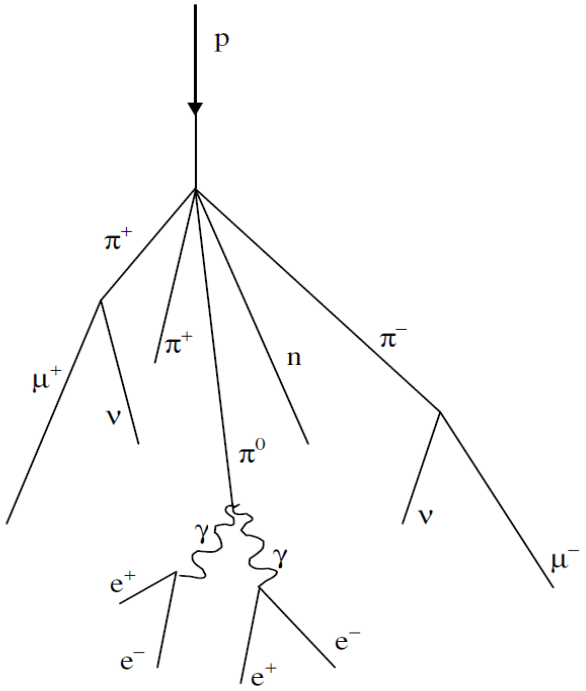

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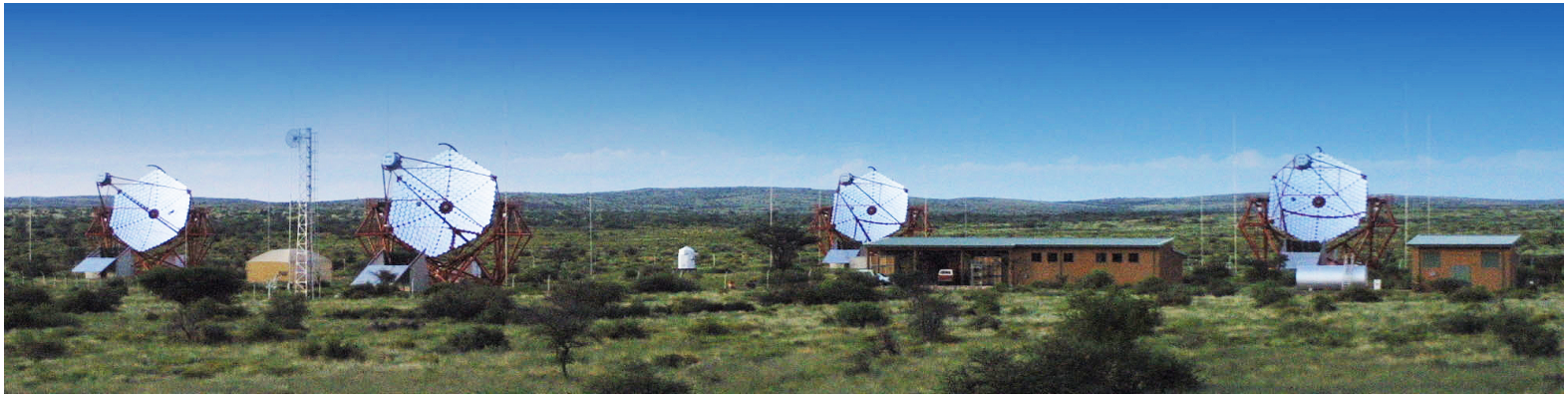

https://www.mpi-hd.mpg.de/hfm/HESS/pages/about/pictures/HESS_IMG/images/HESS-dark-full.jpg

Motivation

- All the shower images have a pattern.

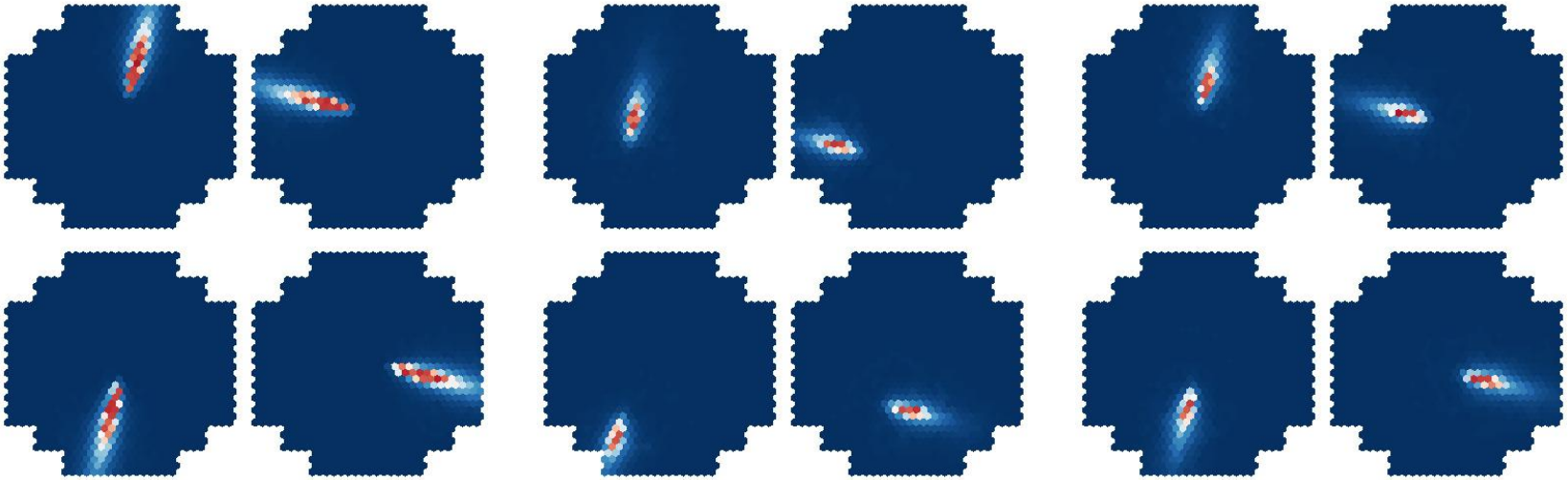

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Figure: Generated telescopic images of air shower initiated by (a) γ, (b) proton and (c) helium.

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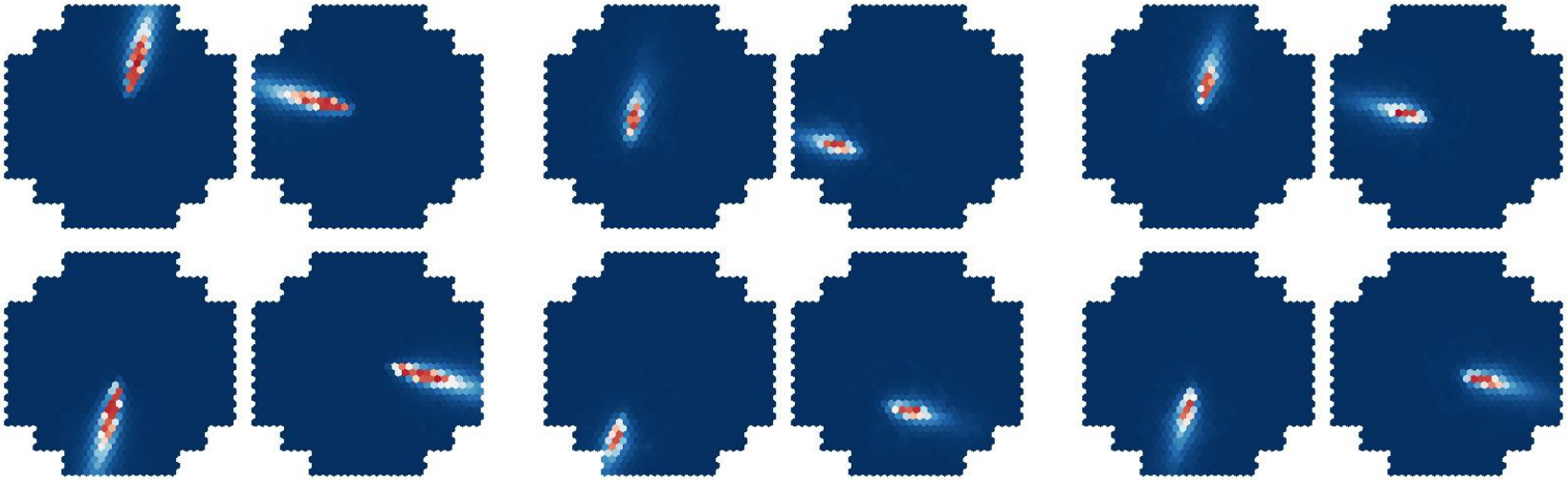

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- Machine learning techniques can be used to extract those patterns.

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- Second, we'll use an anomaly finder algorithm to detect new physics signature in the shower images

Convolutional Neural Network

Building blocks of CNN-

- Convolutional Layer (filters and feature maps)
- Pooling Layer
- Fully Connected Layer

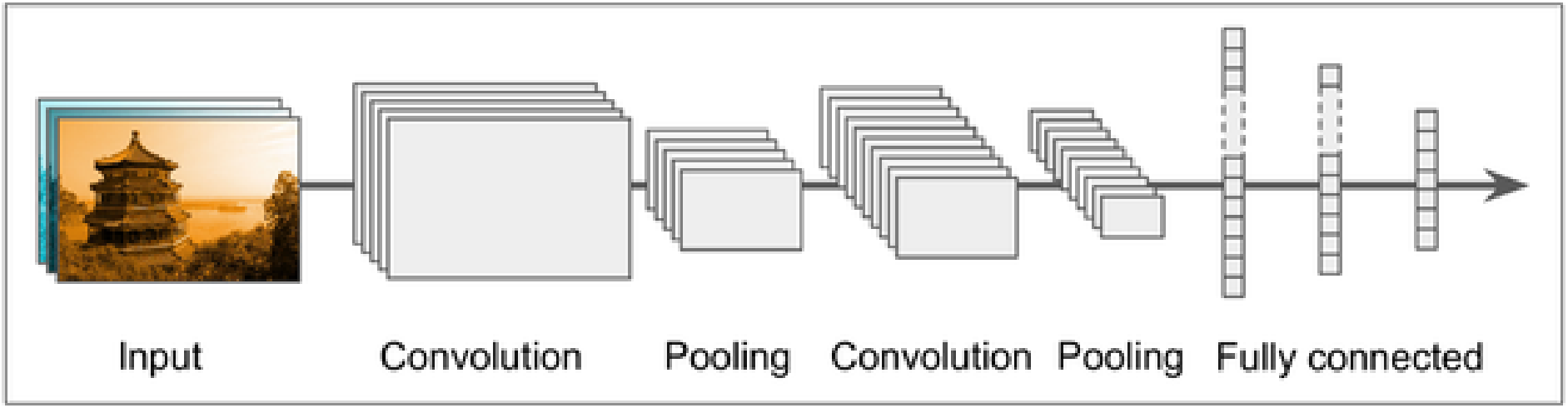


Figure: A typical CNN architecture[1].

[1] Hands-On Machine Learning with Scikit-Learn and TensorFlow, Geron,Aurelien

Autoencoder (used as anomaly finder)

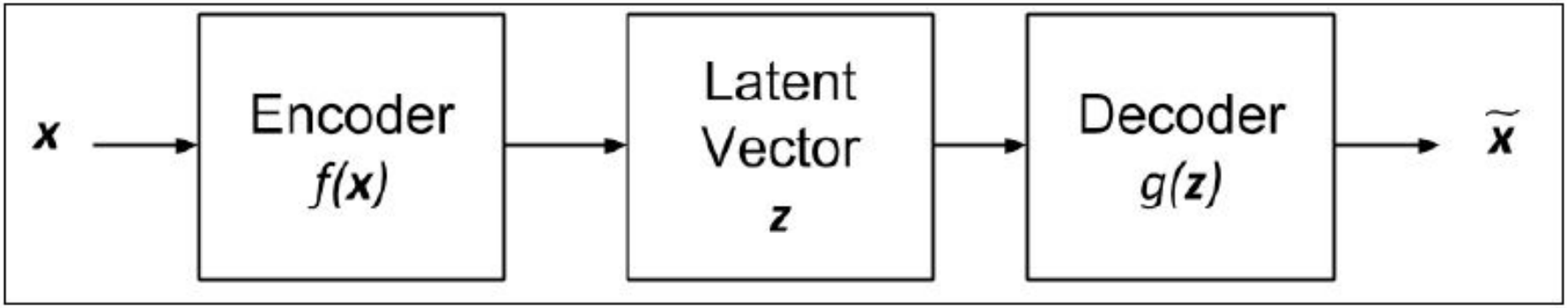
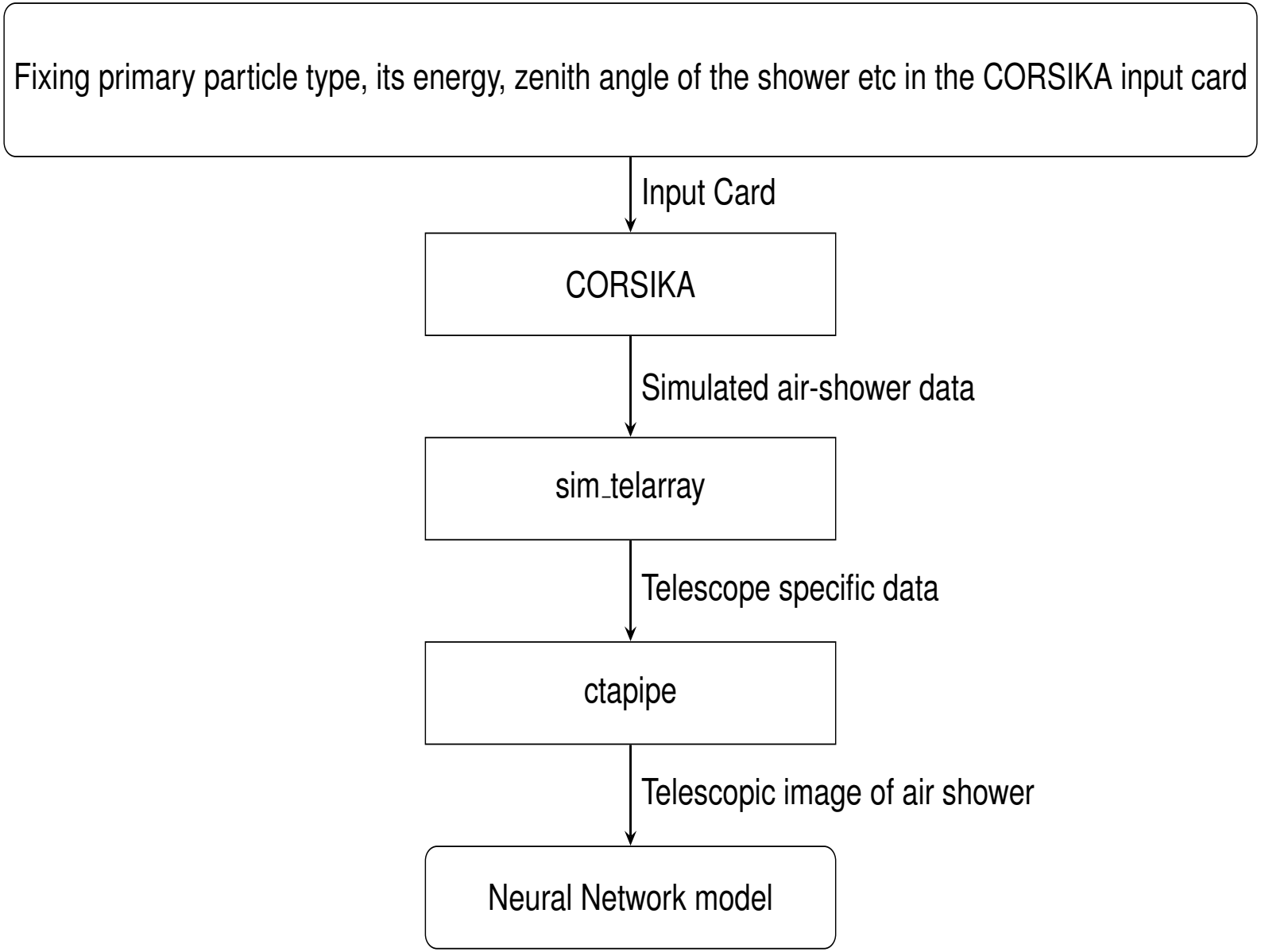


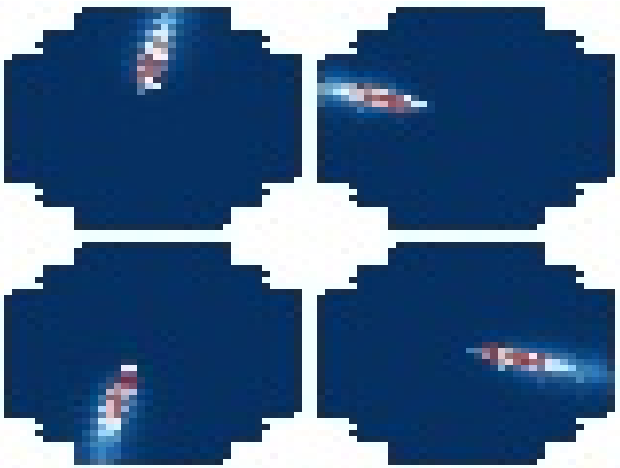
Figure: Schematic representation of an autoencoder architecture

- Autoencoder reconstructs an image.
- On the basis of the extent of reconstruction, we can use it as an anomaly finder.

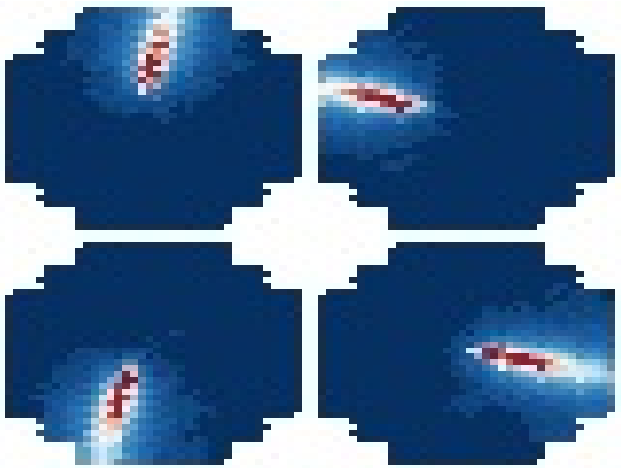
Common methodology



Remapping



(a) Non-remapped γ shower image



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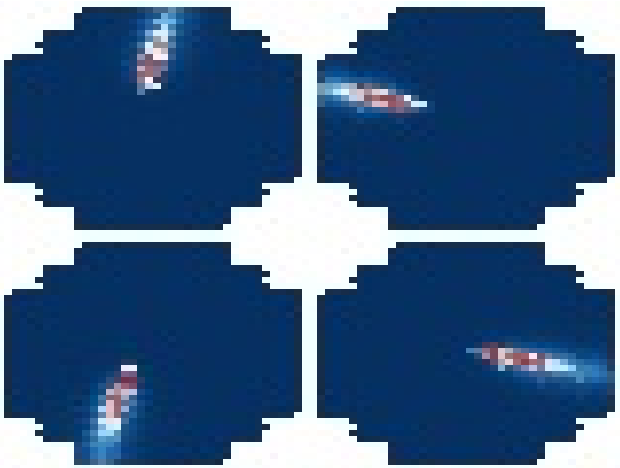

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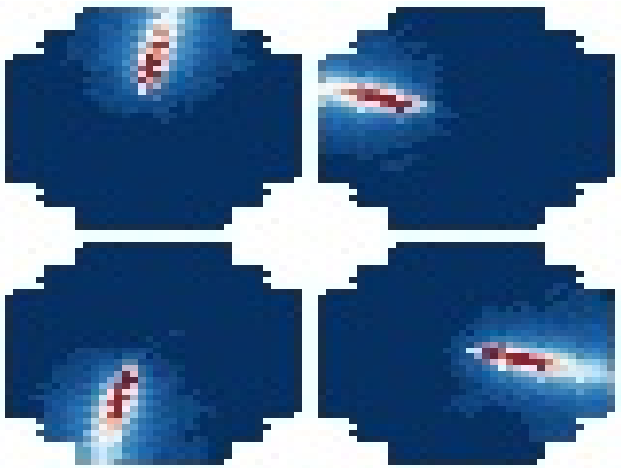

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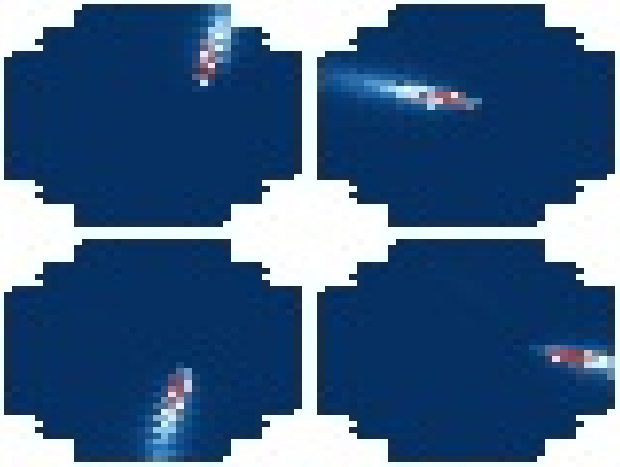
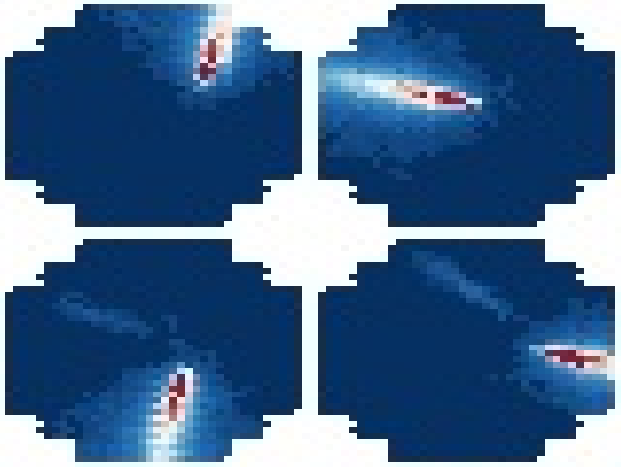


(a) Non-remapped Z' shower image



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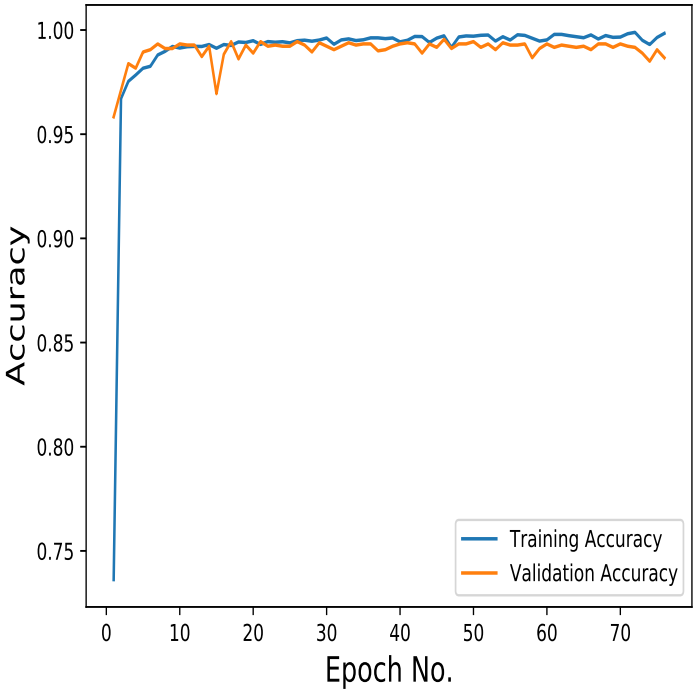
Results - part I



(a) Proton$-\gamma$ classification

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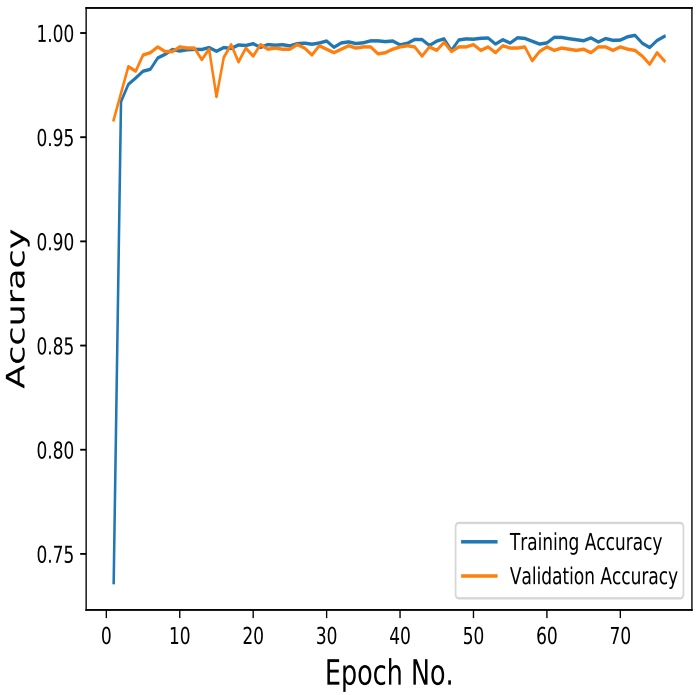

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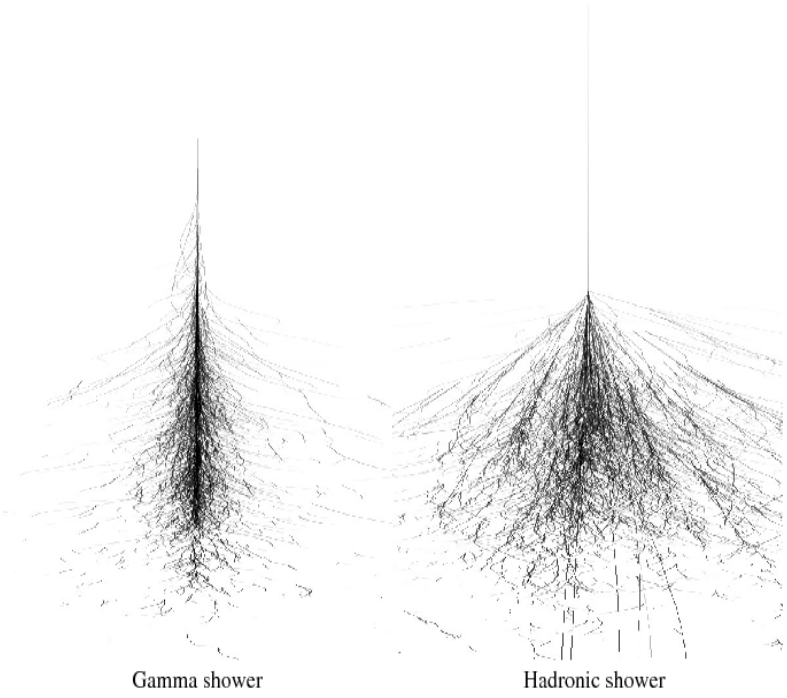


(b) **Left:** Electromagnetic cascade of secondary particles; **Right:** Hadronic cascade of secondary particles

Source of figure 8b:- *Heinrich J. Vlk and Konrad Bernlhr. Imaging Very High Energy Gamma-Ray Telescopes. Exper. Astron., 25:173–191, 2009*

Results - part I (continued)

Binary Classification

Classification	Accuracy		
	Training	Validation	Testing
$\gamma-$proton	0.997	0.996	0.991
$\gamma-$helium	0.995	0.996	0.997
$\gamma-$carbon	0.998	0.999	0.998
proton-helium	0.787	0.764	0.781
proton-carbon	0.967	0.948	0.934
helium-carbon	0.856	0.842	0.847

Table: Training, validation, and testing set accuracy scores for different pairs of SM primaries using our trained binary classifiers.

Results - part I (continued)

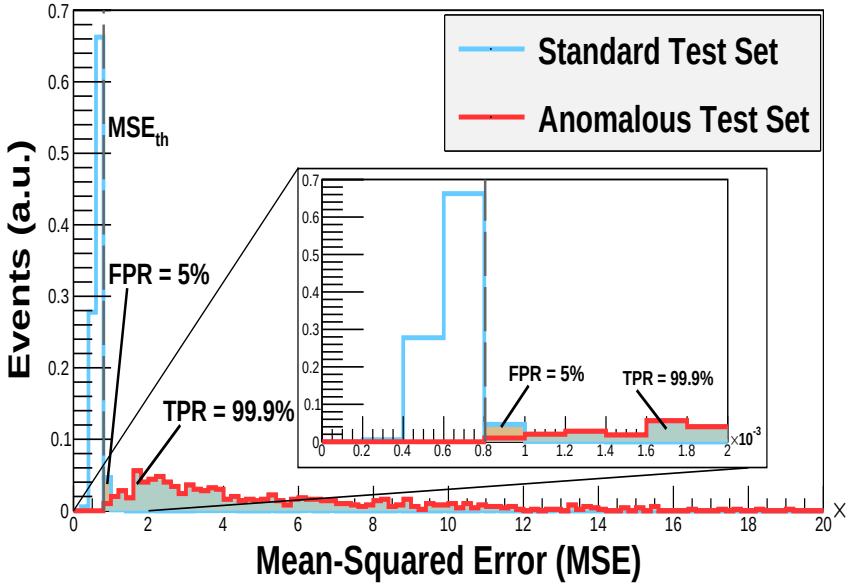
Multilabel Classification

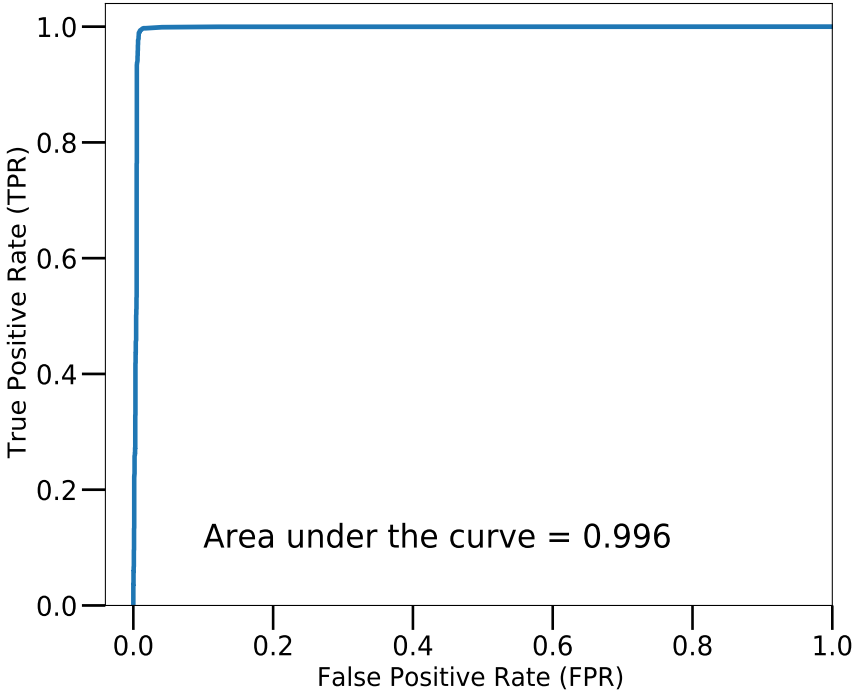
		Predicted Labels			
		γ	proton	helium	carbon
Actual Labels	γ	985	15	0	0
	proton	4	764	208	24
	helium	0	231	564	205
	carbon	0	4	125	871

Table: The confusion matrix for γ-proton-helium-carbon classification computed on the testing data set.

Results - part II

Anomaly detection





(a) ROC curve

Summary

- Every shower image has a particular pattern.
- In our work, we have used Convolutional Neural Network for binary and multi category classification between cosmic showers initiated by different primary nuclei.
- Cosmic ray spectrum extends over a huge range of energies. They provide access to highly energetic phenomena which are not yet accessable at terrestrial experiments like LHC.
- We have proposed the utilization of auto encoders to probe exotic BSM events in the cosmic showers.

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