Quantum generative adversarial networks for gluon-initiated jets generation

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ML
4
SCI

Introduction

HEP Challenge: Monte Carlo simulations are crucial but computationally expensive.

GANs in HEP: Generative Adversarial Networks have shown promise in replicating complex distributions.

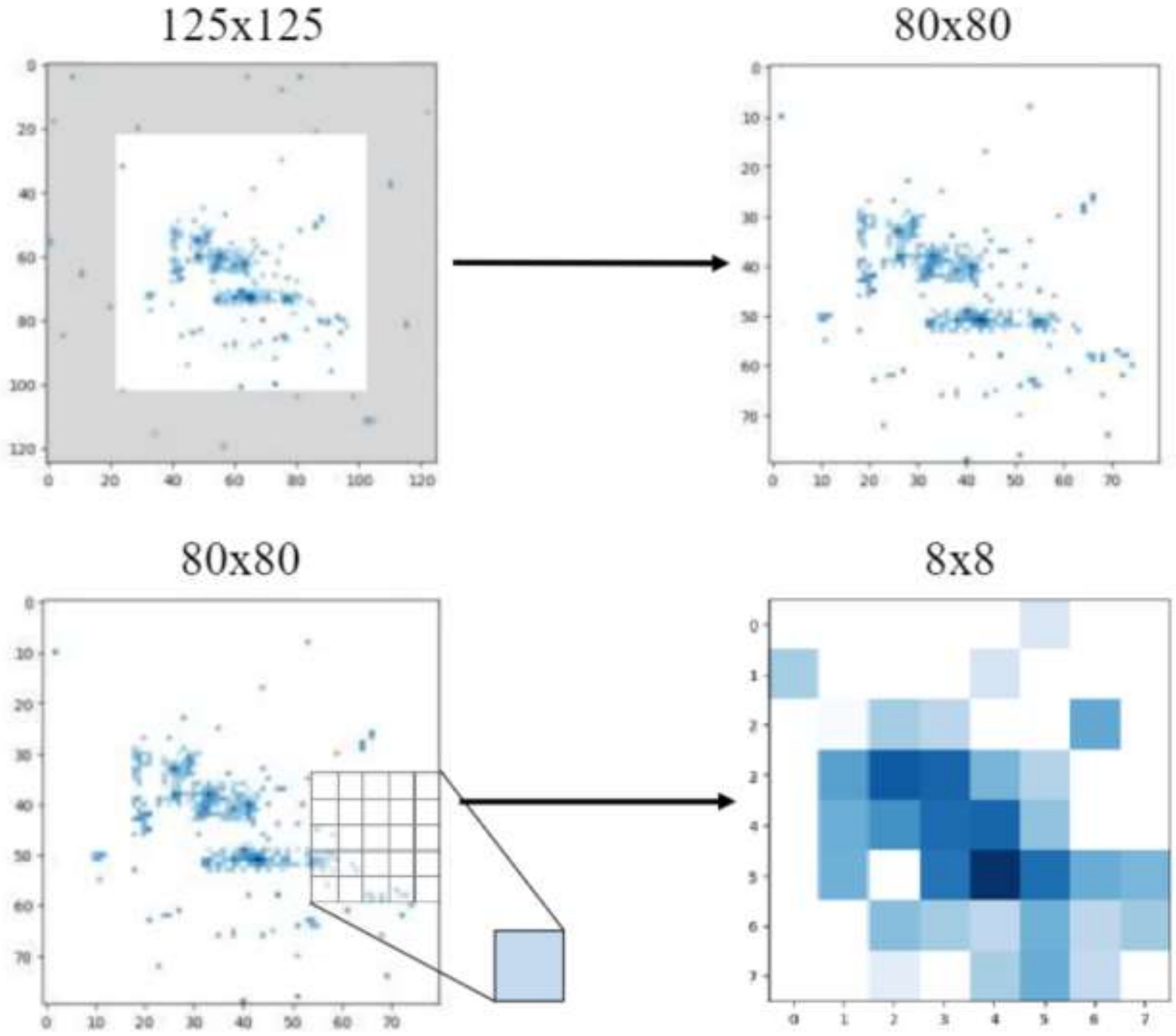
Why Quantum?: Potential for faster convergence, lower resource usage, and learning complex distributions beyond classical capabilities.

Method

Dataset: Gluon-initiated jet images from CMS Open Data (ECAL + HCAL channels).

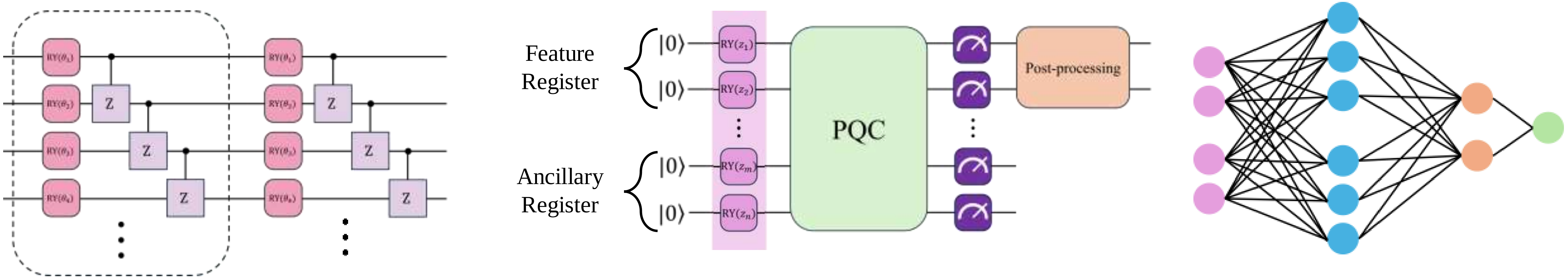
Resolution: Originally 125×125 → cropped (80×80) → sum pooling → final 8×8 images.

Energy Scale: Downscaling preserves overall energy distribution in each channel.



Andrews, M., Alison, J., An, S., Bryant, P., Burkle, B., Gleyzer, S., Narain, M., Paulini, M., Poczos, B. & Usai, E. (2019). End-to-End Jet Classification of Quarks and Gluons with the CMS Open Data. Nucl. Instrum. Methods Phys. Res. A 977, 164304 (2020). https://doi.org/10.1016/j.nima.2020.164304

Method



PQC Quantum Generator Discriminator

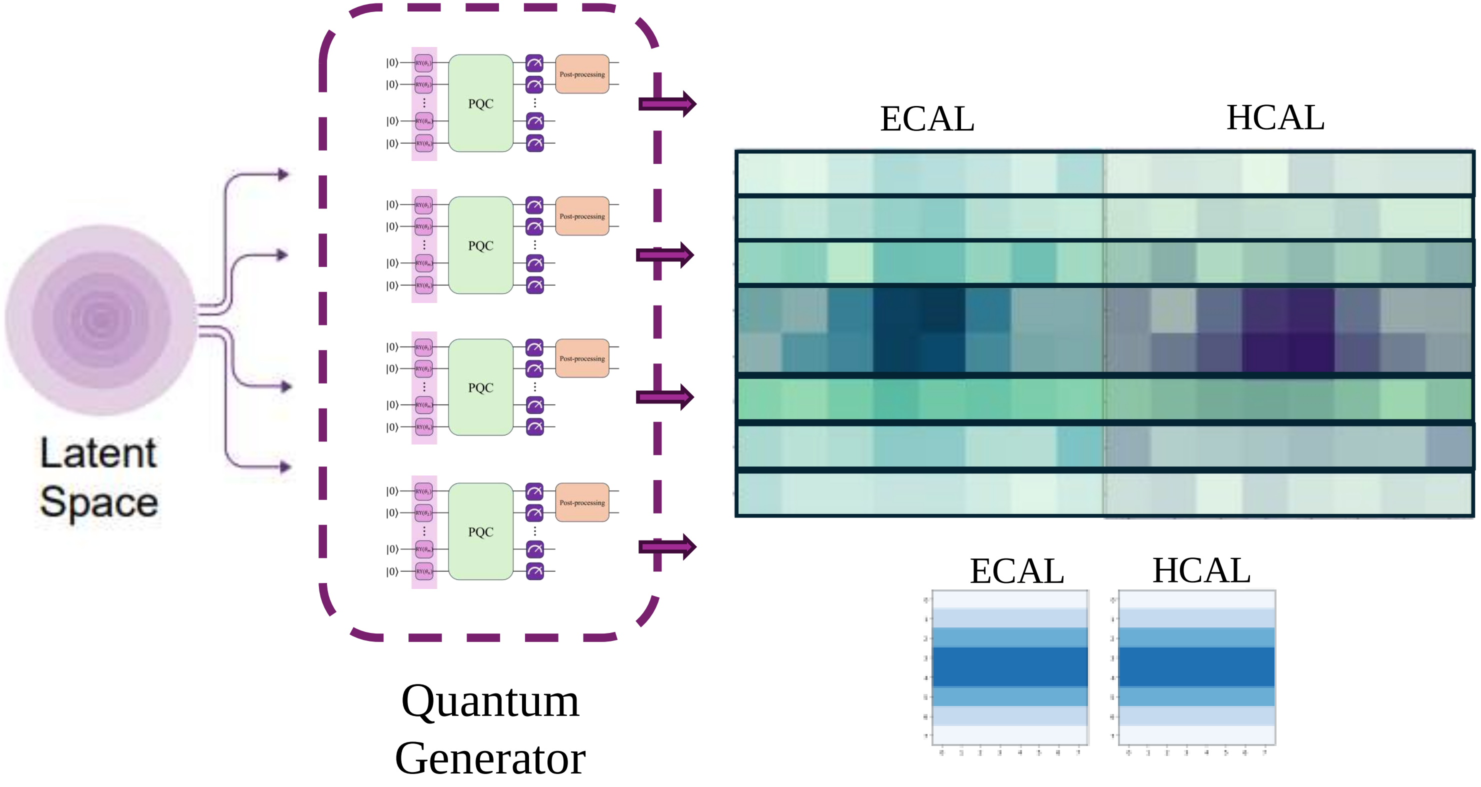
Quantum Generator (PQC):

- Feature qubits + ancillary qubits.
- Parameterized Pauli-Y rotations + Control-Z entangling blocks.
- Outputs measurement probabilities mapped to pixel intensities.

Classical Discriminator:

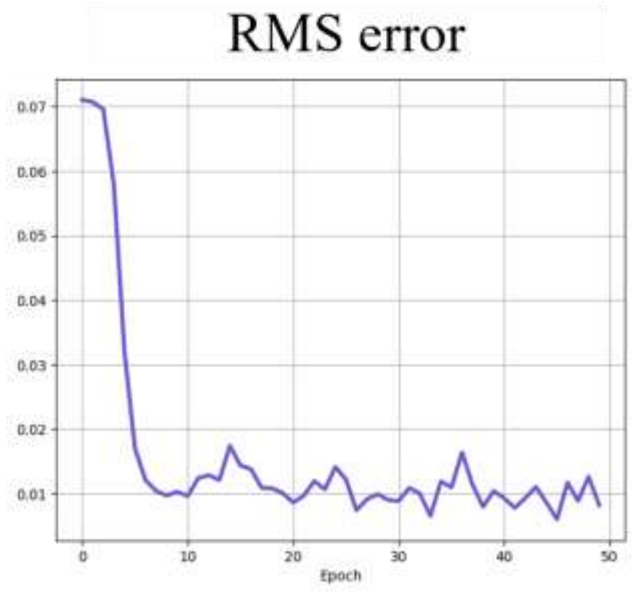
- A dense neural network classifying real vs. generated images.

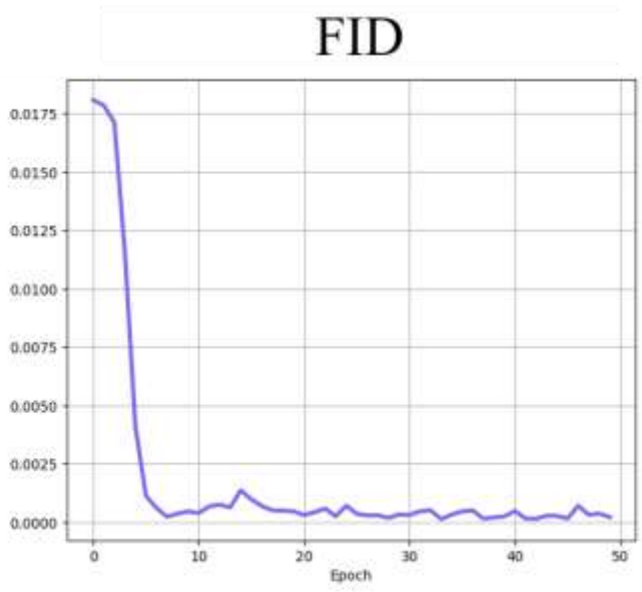
Method

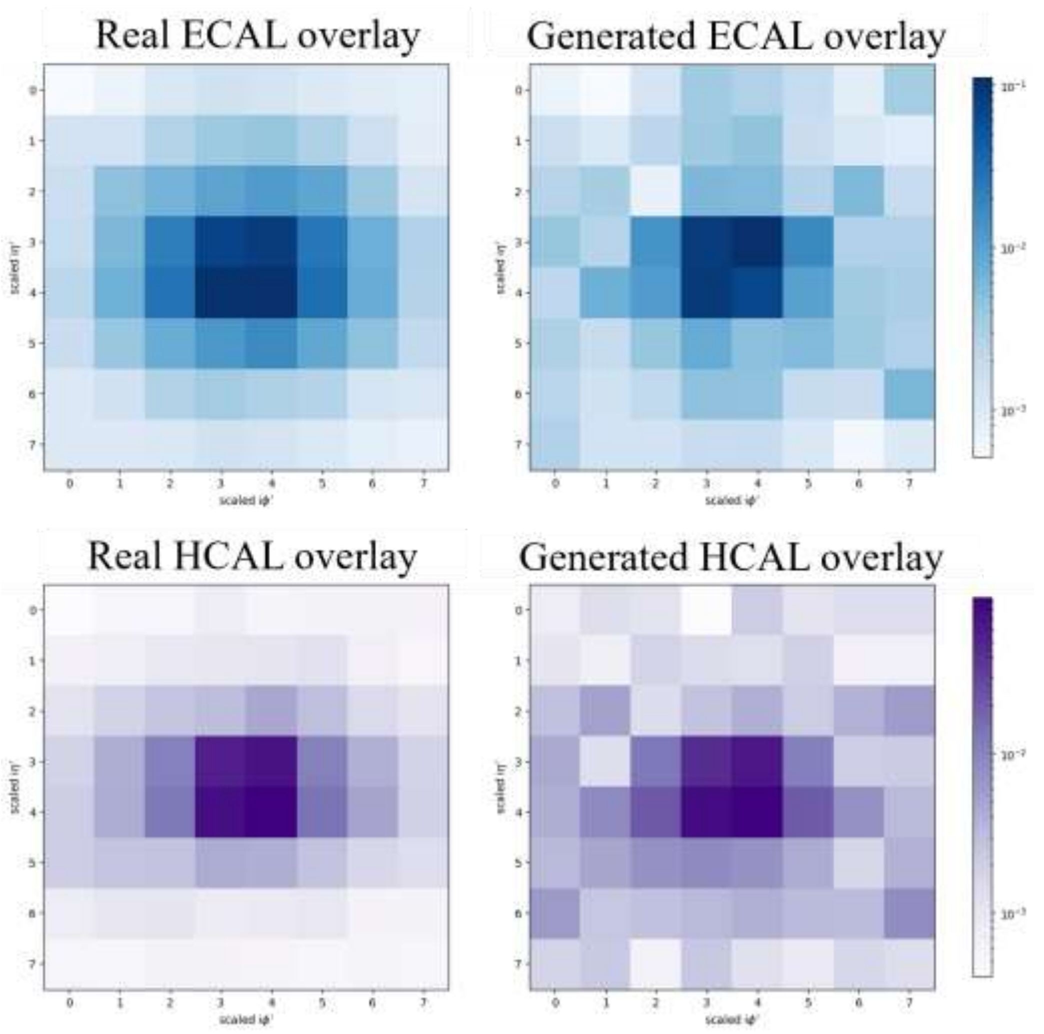


•4 generators (each producing the same patch of the image in both channels), or a single generator with 4 PQCs in parallel.
•Training on 512 images, batch size = 1
•50 epochs, SGD optimizer, learning rates: 0.001 (generator), 0.005 (discriminator).

Results



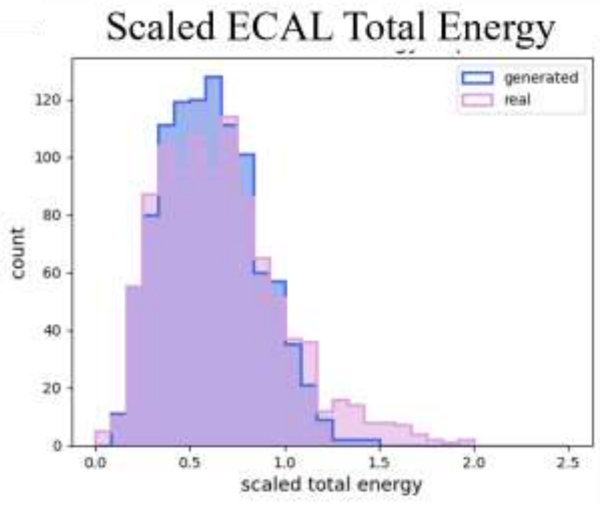


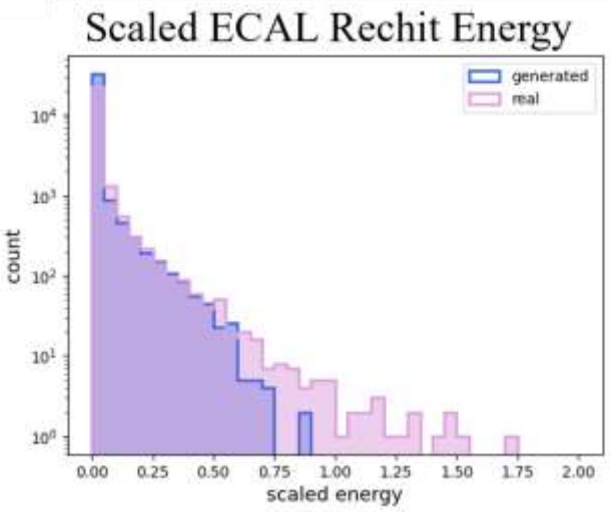


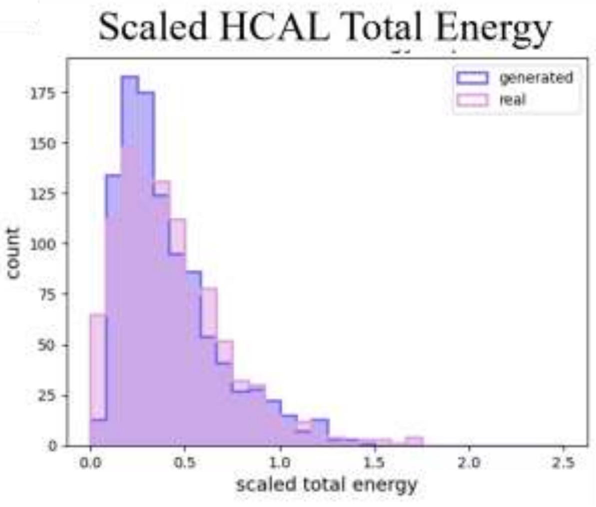
Metrics:
FID and RMSE both converge rapidly.

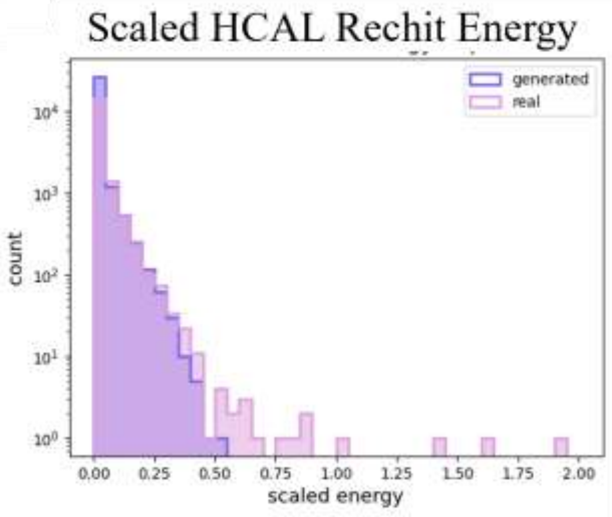
Overlays of generated vs. real images show close agreement in energy deposit patterns.

Results

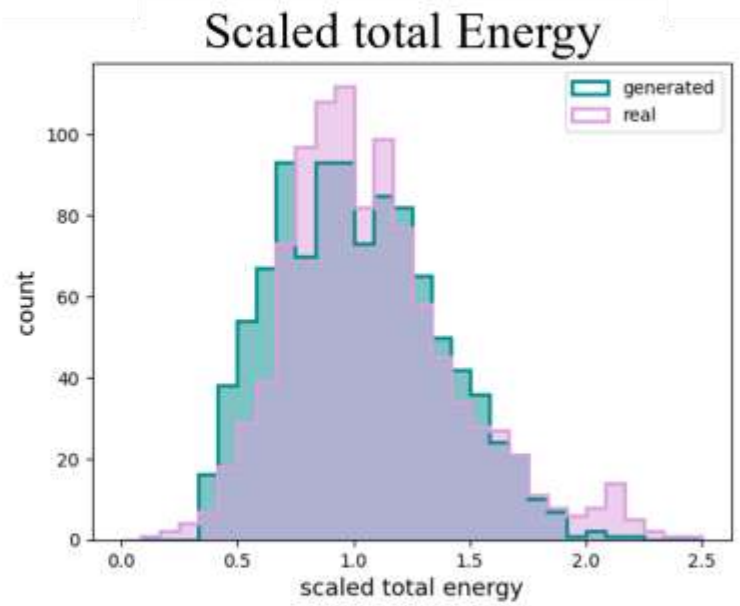








Energy Distributions:
ECAL & HCAL total energy, rechit energy, and combined total all match well between real and generated.



Conclusions

- Demonstrated feasibility of a hybrid QGAN for multi-channel jet image generation.
- Captured realistic energy patterns in both ECAL and HCAL simultaneously.

Next Steps

Scale up dataset size and resolution.

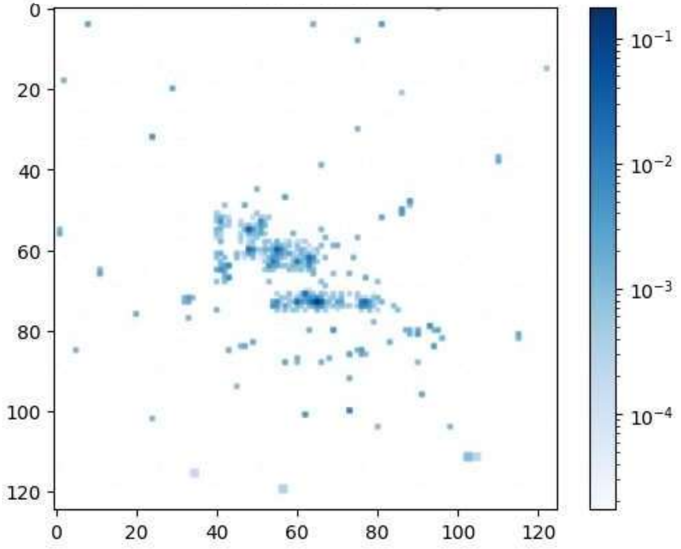
Test on real quantum hardware (noise, limited qubits).

Extend to quark-initiated jets or additional sub-detectors.

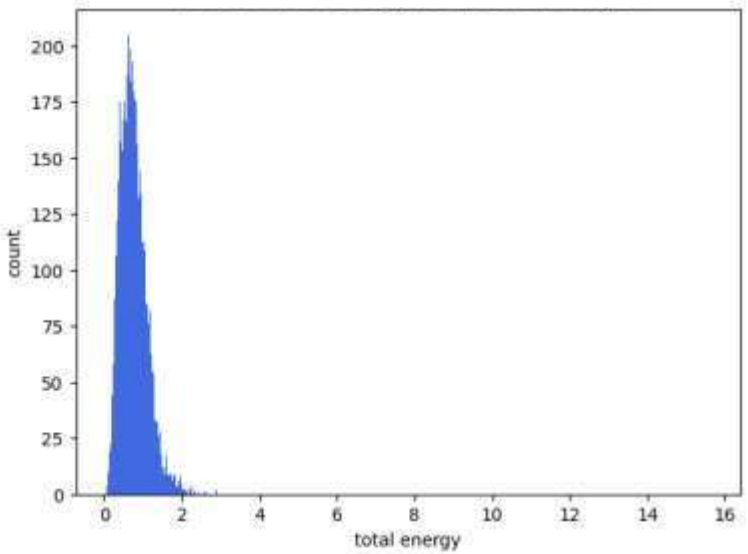
Image preprocessing

1 10000 images

ECAL raw image 125x125



jets Energy deposits



Particle Energy deposits

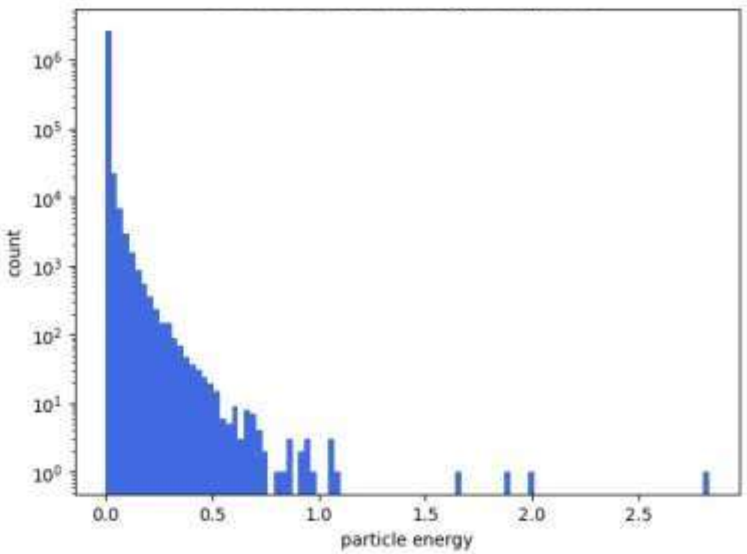
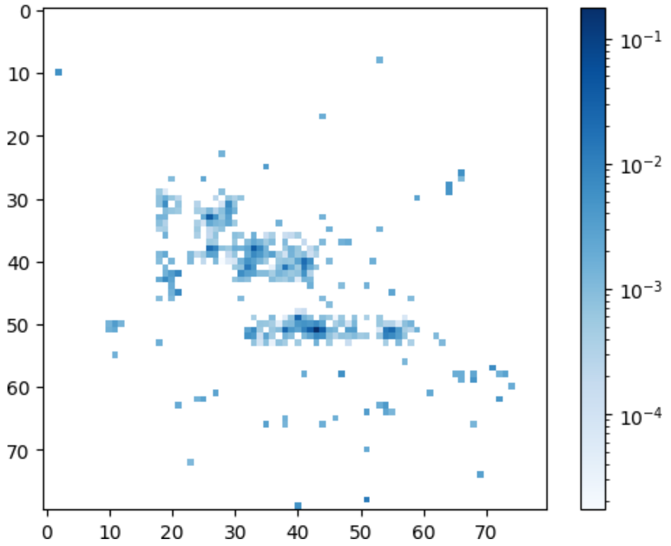


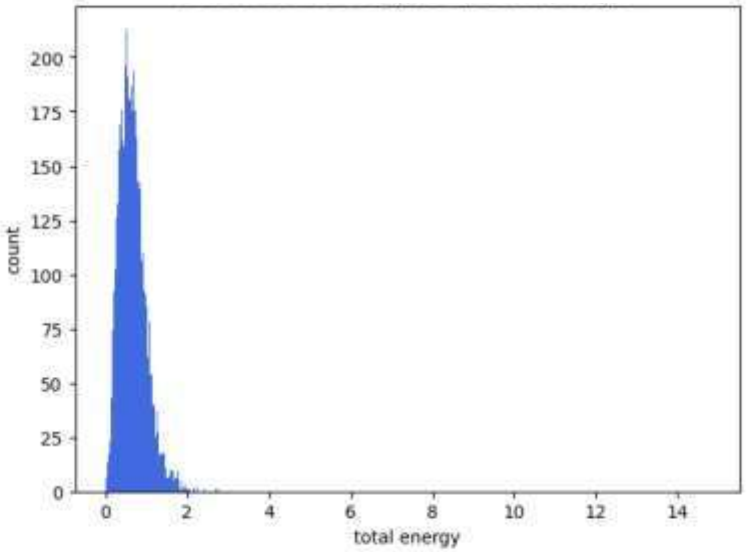
Image preprocessing

2

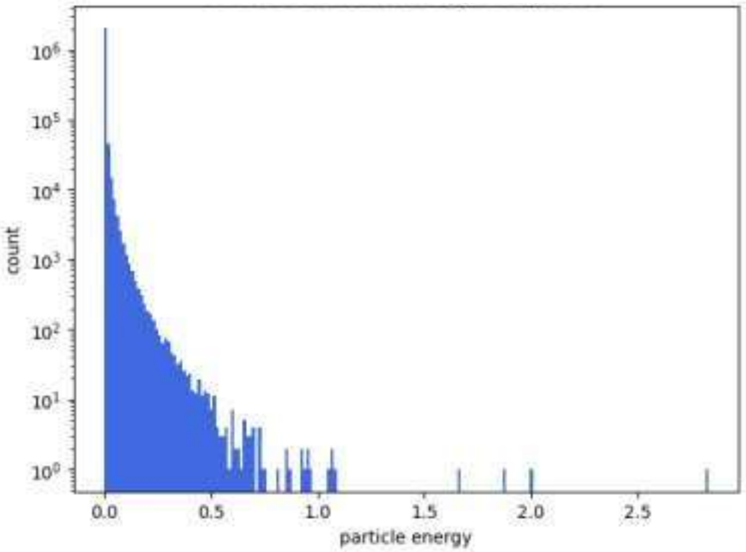
ECAL cropped image 80x80



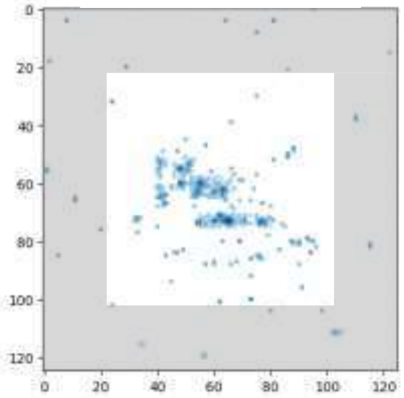
Cropped jets Energy deposits



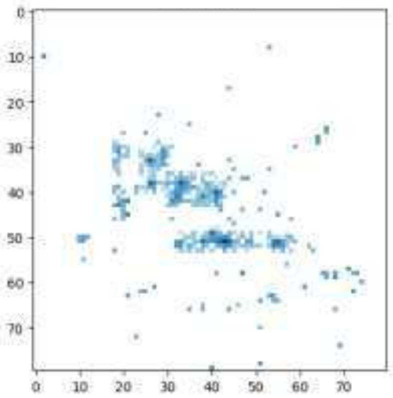
Cropped Particle Energy deposits



125x125



80x80



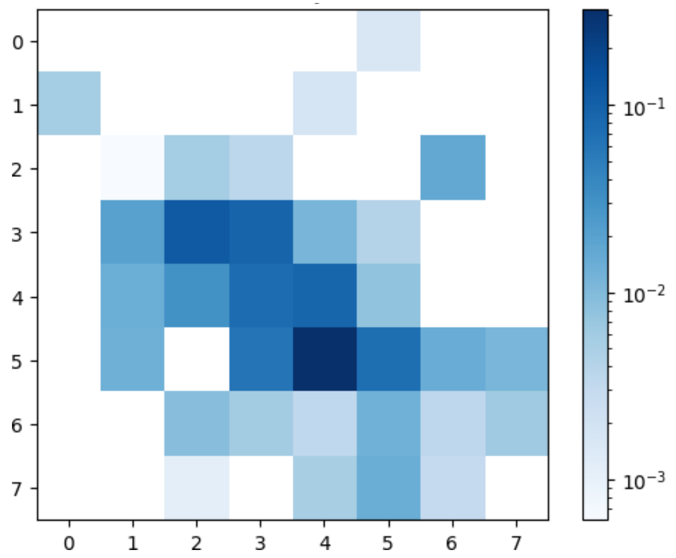
- The cropped jets energy deposits distribution change respect to raw images. The cropped jets has less energy because the border pixels are ignored.

- Cropped particle energy deposits distribution has a small change respect to raw images. There are less particles with small energies.

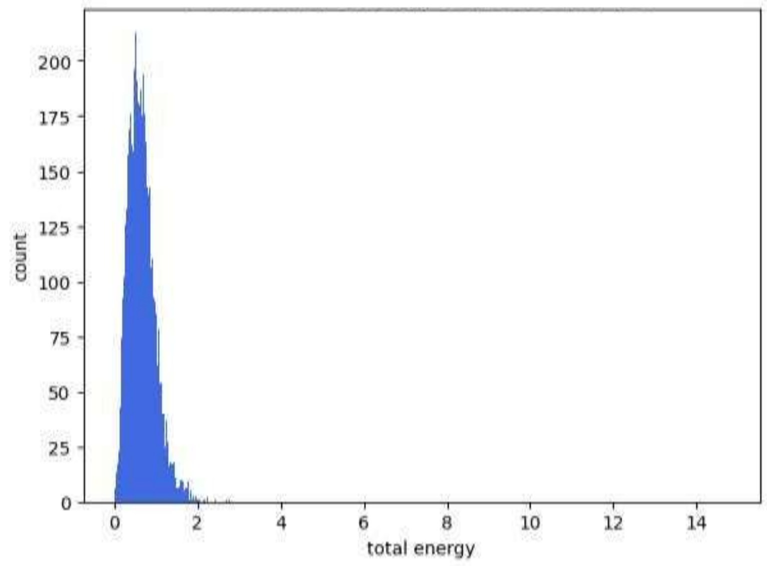
Image preprocessing

3

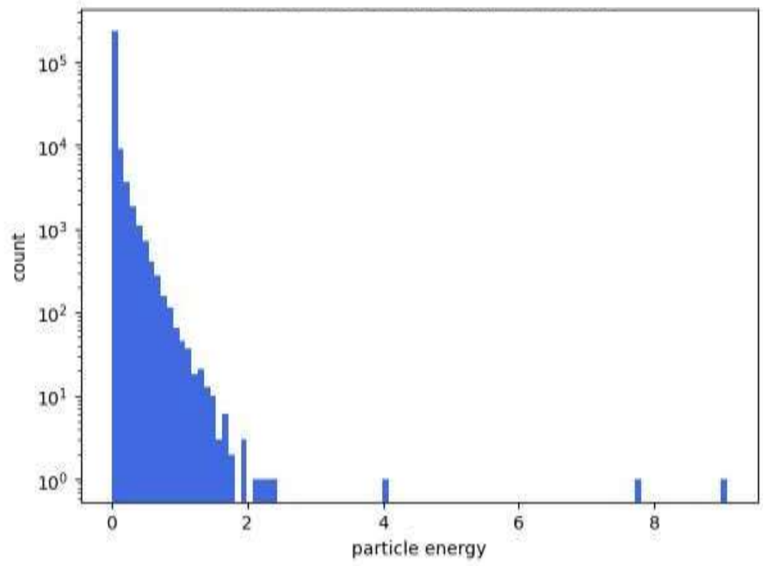
ECAL Sum pooled image 8x8



Sum pooled jets Energy deposits

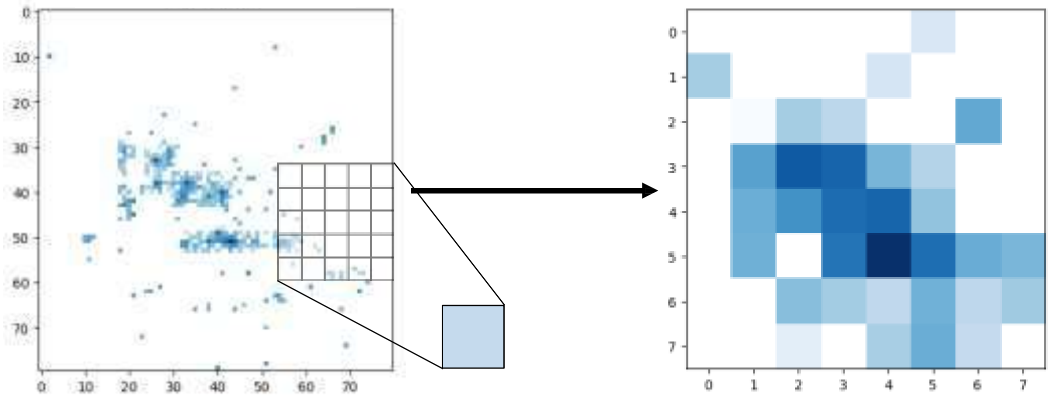


Sum pooled Particle Energy deposits



80x80

8x8

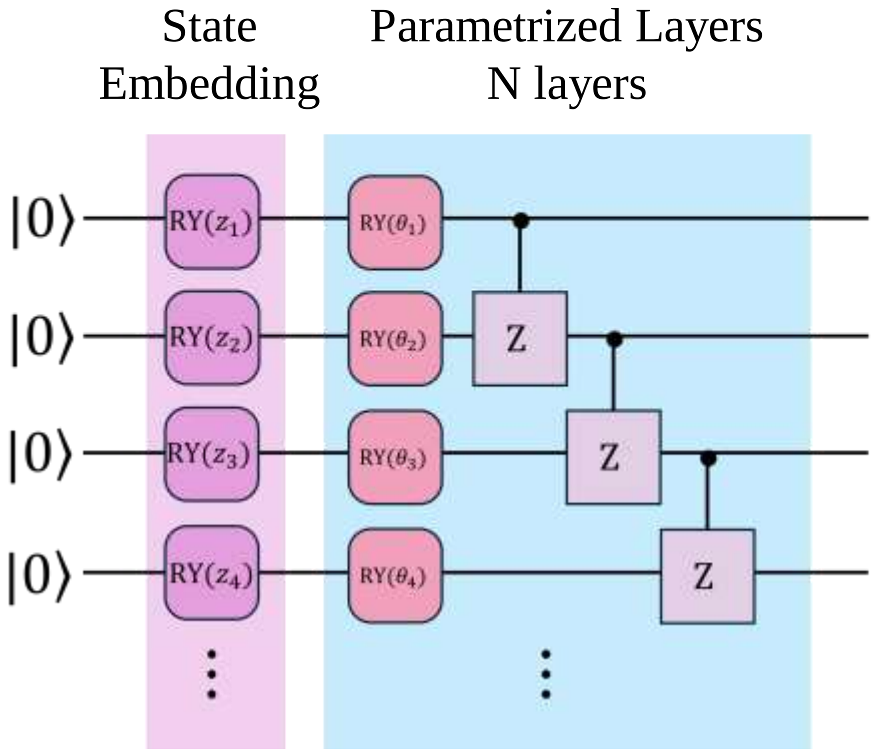


Sum Pooling

- Kernel: 10x10
- Stride: 10
- Padding: 0
- Sum the values of all pixels in the kernel

- The sum pooled jets energy deposits distribution does not change respect to cropped images.
- Sum pooled Particle energy deposits distribution changes, the pixels from 8x8 images has larger values than 80x80.

State Embedding and parametrized layers



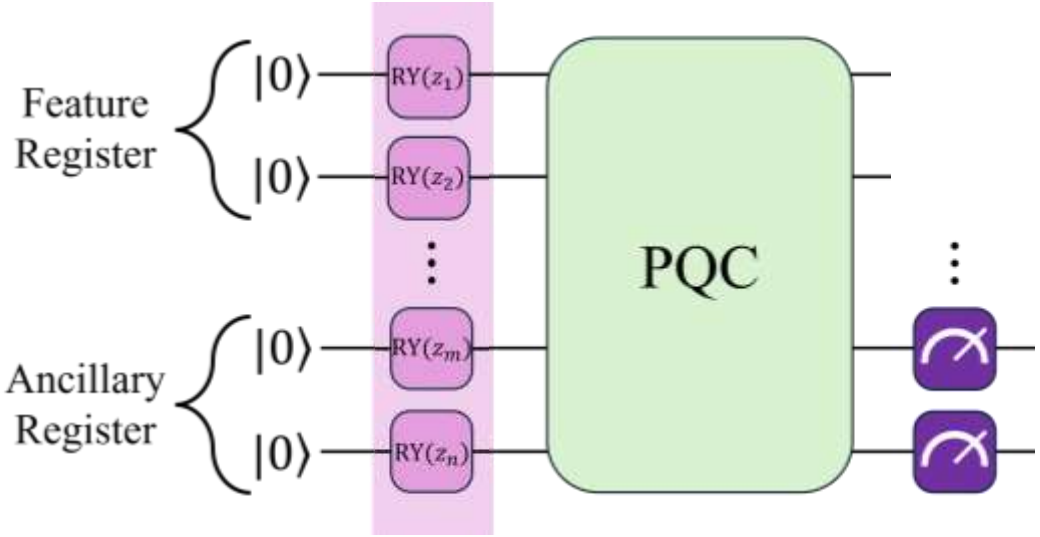
For a given sub-generator, the pre-measurement quantum state is given by

$$|\Psi(z)\rangle = U_G(\theta)|\boldsymbol{z}\rangle$$

Where:

$$\boldsymbol{z} \in \mathbb{R}^N \qquad \boldsymbol{z}_{\mathrm{i}} \in [0, \pi/2)$$

Non-Linear Transformation



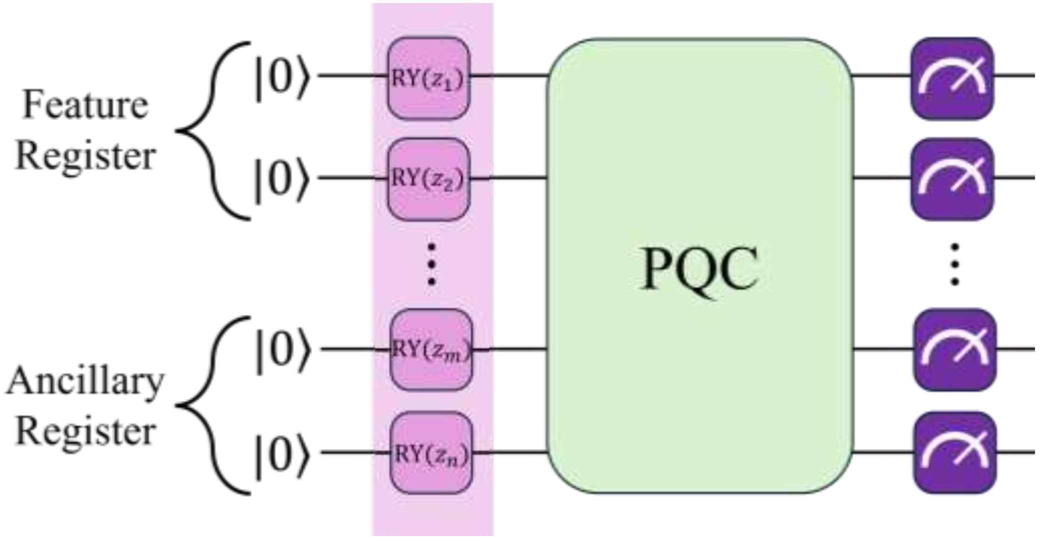
To introduce a non-linear transformation, we perform a partial measurement on only some of the qubits in the system.

$$\Pi = (|0\rangle\langle 0|)^{\otimes N_A}$$

After this measurement, we trace out the ancillary subsystem A, obtaining the reduced density matrix:

$$\rho(\boldsymbol{z}) = \frac{\mathrm{Tr}_{\mathcal{A}}(\Pi \otimes \mathbb{I}|\Psi(\boldsymbol{z})\rangle\langle\Psi(\boldsymbol{z})|)}{\langle\Psi(\boldsymbol{z})|\Pi \otimes \mathbb{I}|\Psi(\boldsymbol{z})\rangle}$$

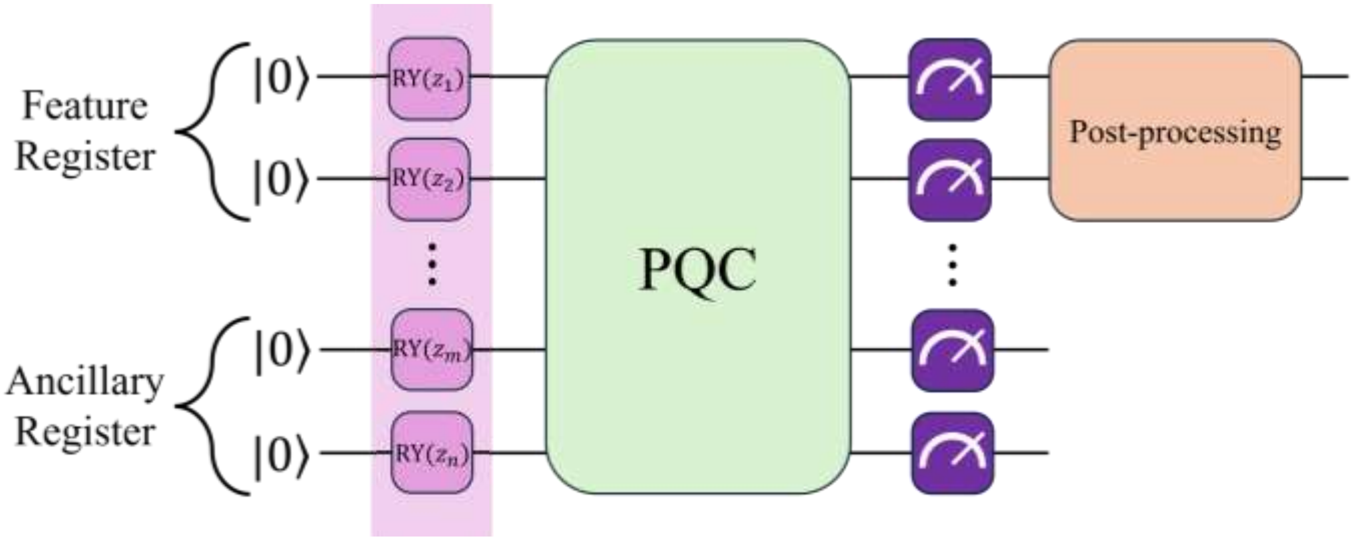
Non-Linear Transformation



After measurement and tracing out the ancillary qubits, we have a reduced state $\rho(z)$. To get the final output, we compute the probability of measuring the remaining data qubits in different basis states:

$$\boldsymbol{g}^{(i)} = [P(0), P(1), \ldots, P(2^{N-N_A} - 1)]$$

Post processing



To scale the output so that it fits within the range needed for energy deposits values, we divide by a factor

$$\tilde{\boldsymbol{x}}^{(i)} = \frac{\boldsymbol{g}^{(i)}}{\boldsymbol{y}} \qquad \boldsymbol{y} \in [\mathbf{0}, \mathbf{1}]$$

Therefore, the final image is given by:

$$\tilde{\boldsymbol{x}} = [\tilde{\boldsymbol{x}}^{(1)}, \ldots, \tilde{\boldsymbol{x}}^{(N_G)}]$$