Predicting flow coefficients for heavy ion collisions with deep learning

Anna Binoy Arpan Maity

National Institute of Science Education and Research Bhubaneswar

October 2, 2023

Introduction

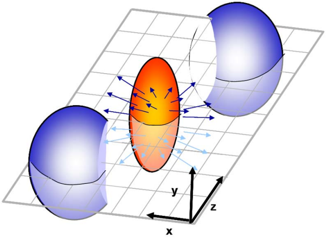

Figure 1: Geometry of heavy-ion collision[1]

- QCD (Quantum Chromodynamics) is the theory of strong interaction explaining how protons and neutrons are bound inside nuclei.
- Quark-Gluon Plasma (QGP), a high-energy state of deconfined quarks and gluons, believed to exist shortly after the Big Bang.
- Heavy Ion Collisions is Used to create QGP conditions in the laboratory.
- Flow coefficients are Observables used to study QGP expansion.

[1] Jacazio, N. Production and nuclear modification factors of pions, kaons and protons in pp and AA collisions at the LHC. PhD thesis, Bologna U., 2019

Dataset

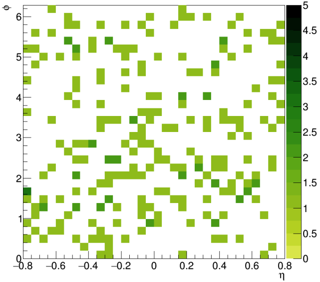

Figure 2: Charged multiplicity in η and ϕ

- Monte Carlo event generator Pythia (version 8.309) was used to simulate Pb-Pb (5.02 TeV) and Xe-Xe (5.44 TeV) collision.
- Specific criteria were applied, including cuts on η (-0.8 to 0.8), transverse momentum ($0.2 < p_T < 5$ GeV/c), and minimum charged particle multiplicities (15 for Xe-Xe and 25 for Pb-Pb).
- The model takes 2D histogram images of charged particle distributions in the η and ϕ space as input.
- The dataset(10k) was split into three parts for training, validation, and testing, with an 8:1:1 ratio.

Model

- Two convolutional layers:
  - First Layer: 16 output channels, 3x3 kernel, ReLU activation.
  - Second Layer: 4 output channels, 3x3 kernel, ReLU activation, followed by batch normalization.
- Average pooling (2x2) for downsampling.
- Fully connected layers:
  - First two layers: 256 nodes each.
  - Next three layers: 128 nodes each.
  - Sixth layer: 32 nodes followed by output layer.
- Stochastic Gradient Descent (SGD) optimizer with LR=0.01, Mean Squared Error (MSE) and Mean Squared Logarithmic Error (MSLE), trained for 50 to 100 epochs for different systems.

Results

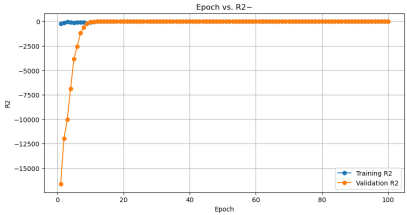

Figure 3: Epoch vs R^2 for Xe-Xe at 5.44 TeV Centre of Mass Energy

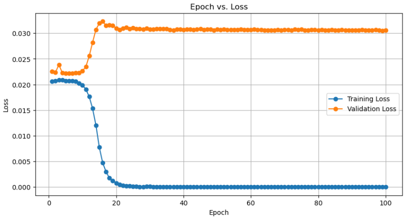

Figure 4: Epoch vs MSE Loss for Xe-Xe at 5.44 TeV Centre of Mass Energy

Results

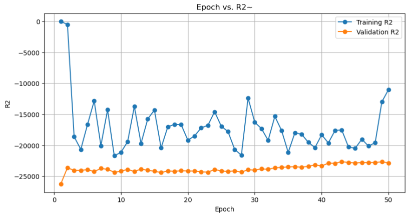

Figure 5: Epoch vs R^2 for Pb-Pb at 5.02 TeV Centre of Mass Energy

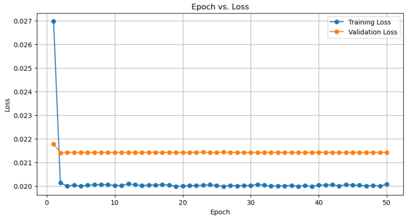

Figure 6: Epoch vs MSE Loss for Pb-Pb at 5.02 TeV Centre of Mass Energy

Future Plan

- Enhancing CNN for better elliptic flow coefficient prediction.
- Exploring other methods for improved predictions.
- Assessing impact of larger bin width for η and ϕ in image generation.
- Image generation with diffusion models (DDPM and DDIM).
- Investigating prediction of higher-order flow coefficients.
- Training models for different centrality classes based on impact parameter.
- Considering glauber models for elliptic flow analysis.

References

- Vinicius Mikuni, et al.,“Fast Point Cloud Generation with Diffusion Models in High Energy Physics.”, arXiv:2304.01266
- Neelkamal Mallick, et al.“Estimating elliptic flow coefficient in heavy ion collisions using deep learning” ,Phys. Rev. D,105:11(2022)
- Matthew Leigh, et al.“PC-JeDi: Diffusion for Particle Cloud Generation in High Energy Physics.” , arXiv:2303.05376
- Saldic, Z. A proposed model to estimate flow coefficients from charged-particle densities using Deep Learning, 2020
- Hirvonen, H., Eskola, K. J., and Niemi, H. Deep learning for flow observables in ultrarelativistic heavy-ion colli- sions, Phys. Rev. C, 108:034905(2023)

Thank You!