A QGP Trigger for the CBM Experiment based on Artificial Neural Networks

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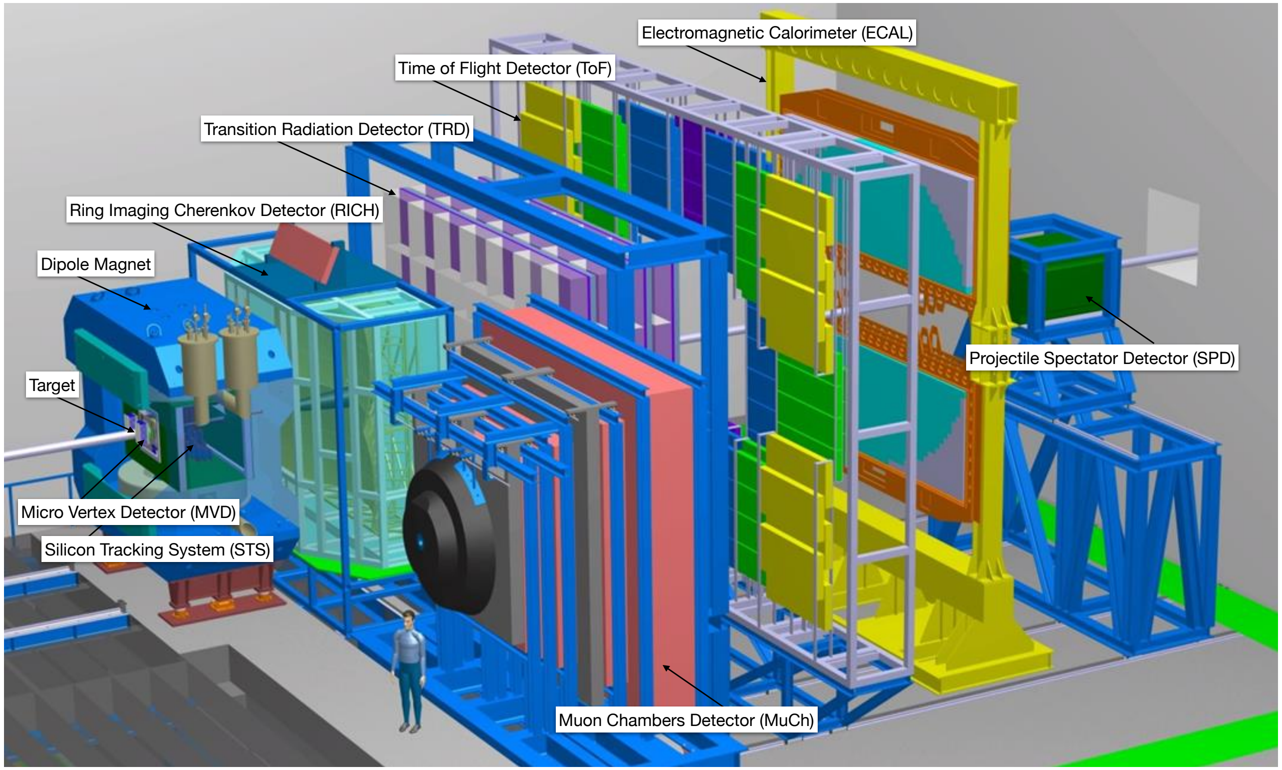
CBM Experiment

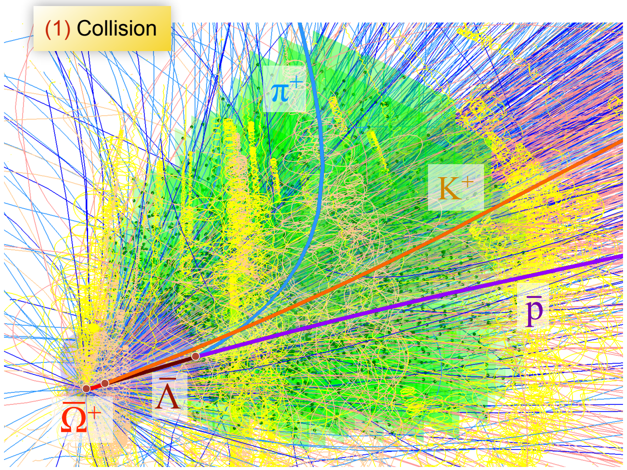
- Compressed Baryonic Matter (CBM) is currently being constructed at FAIR accelerator facility in Darmstadt.
- Highest baryon densities will be created and the properties of super-dense nuclear matter will be explored.
- The experimental program of CBM is to measure a large number of observables at various beam energies and different collision systems. Many of them are extremely rare, like multi-strange anti-hyperons, open and hidden charm.

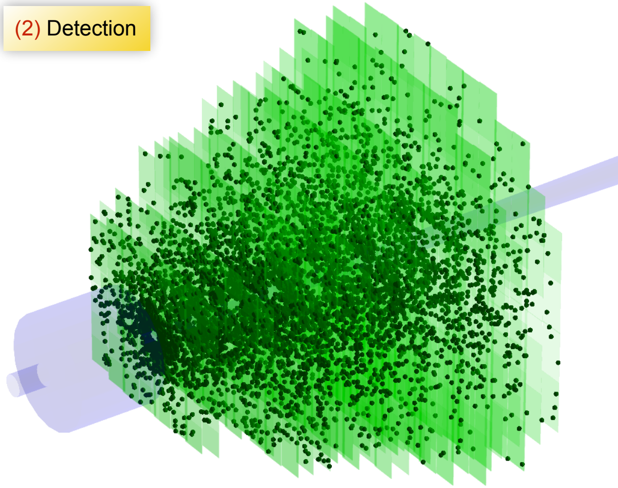


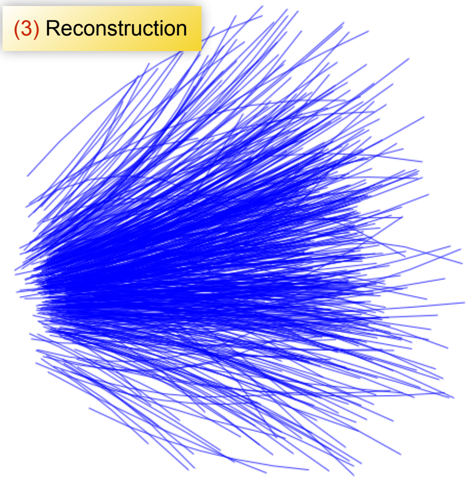
The CBM setup: target, dipole magnet, Micro Vertex Detector (MVD), Silicon Tracking System (STS), Ring Imaging Cherenkov (RICH), Muon Chambers (MuCh), Transition Radiation Detector (TRD), Time-Of-Flight (TOF), Electromagnetic Calorimeter (ECAL), Projectile Spectator Detector (PSD)

Such a multifunctional and versatile structure of the detector setup will make it possible to study the most complex processes in the collision of heavy ions

Reconstruction Challenge in CBM





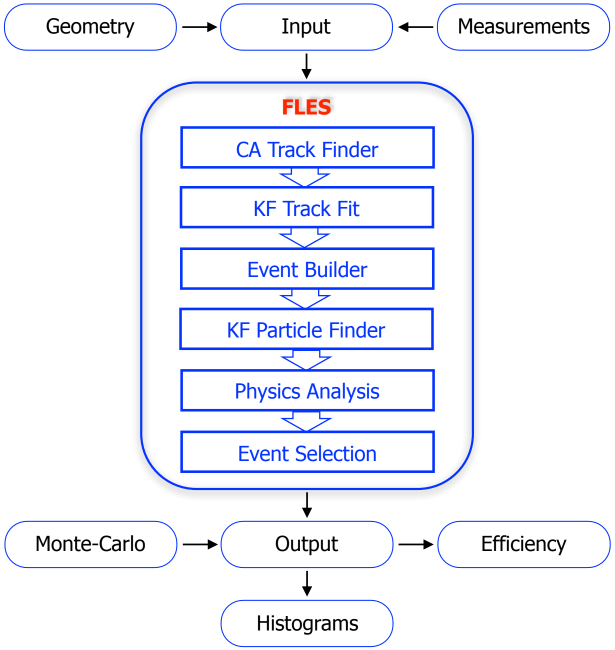


- Future fixed-target heavy-ion experiment at FAIR
- Explore the phase diagram at high net-baryon densities
- 10^7 Au+Au collisions/sec
- ~ 1000 charged particles/collision
- Non-homogeneous magnetic field
- Double-sided strip detectors
- 4D reconstruction of time slices.

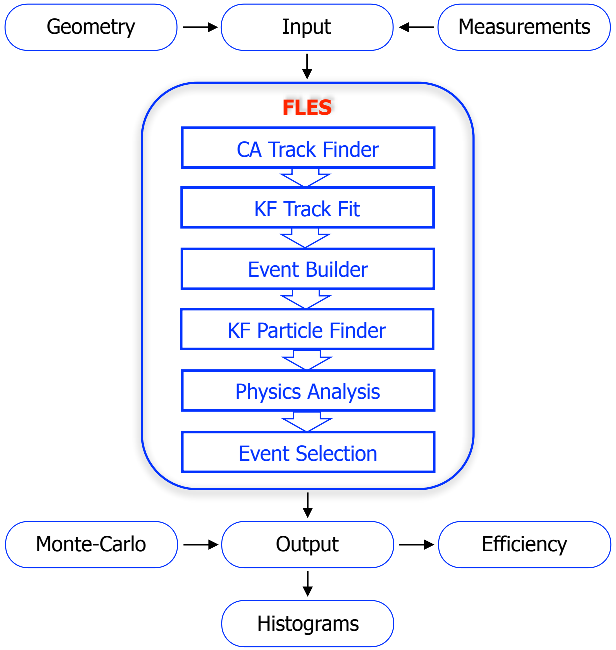
The full event reconstruction will be done on-line at the First-Level Event Selection (FLES) and off-line using the same FLES reconstruction package.

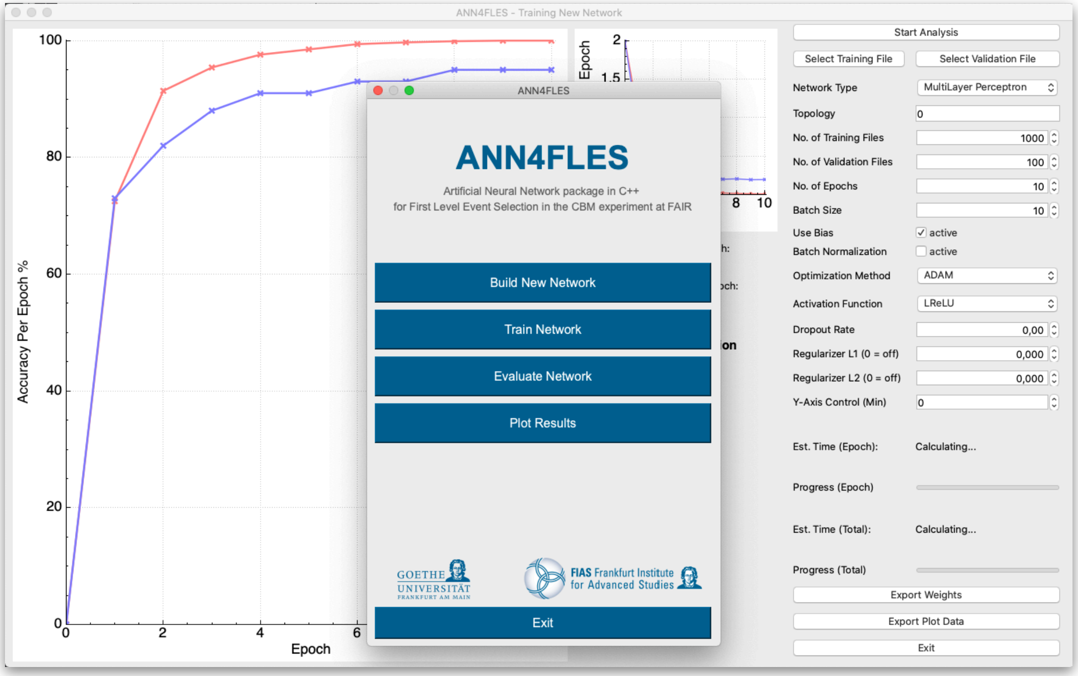
- Cellular Automaton (CA) Track Finder
- Kalman Filter (KF) Track Fitter
- KF short-lived Particle Finder

All reconstruction algorithms are vectorized and parallelized.



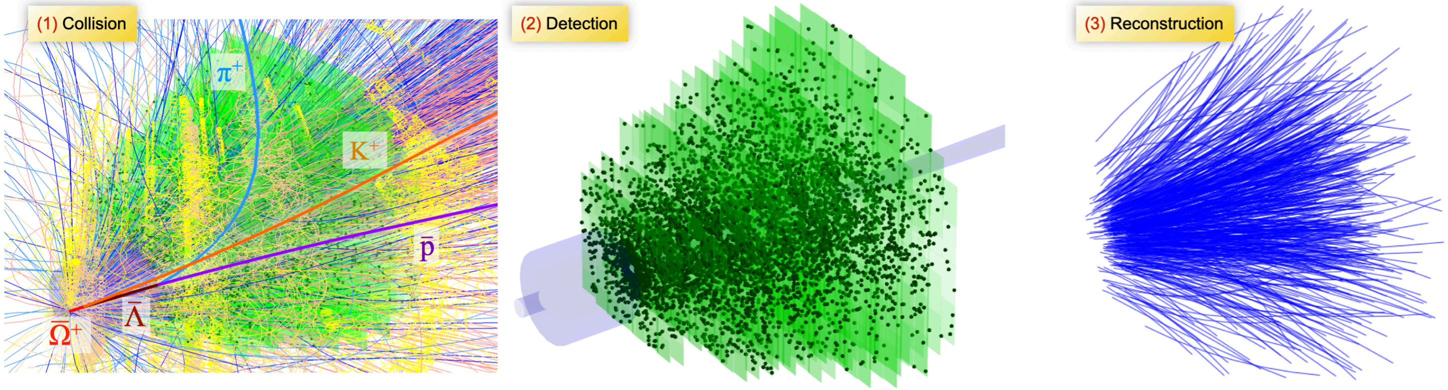
ANN4FLES: ANNs for First Level Event Selection



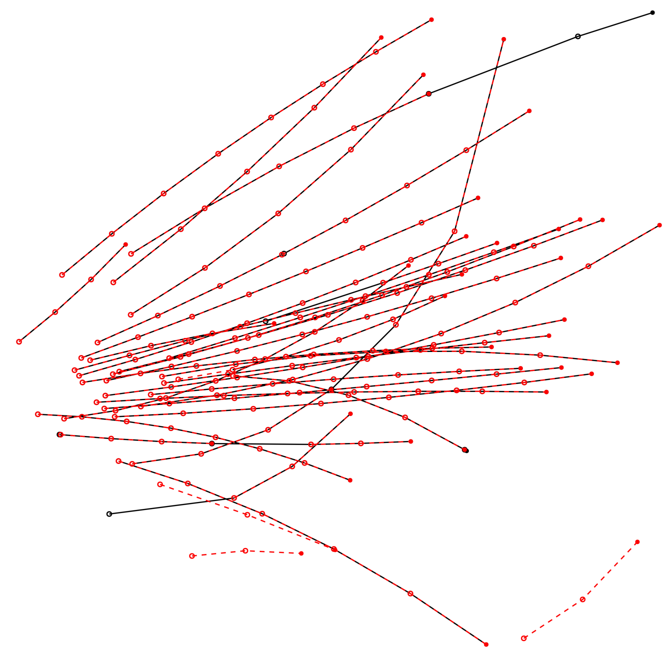


- ANN4FLES is a fast **C++ package** designed for use of Artificial Neural Networks (ANN) in the CBM experiment.
- It provides a variety of network architectures with **minimal additional programming** required.
- The package includes a Graphical User Interface (GUI) for **network selection** and **hyperparameter** adjustment.
- **Implemented networks** in **ANN4FLES** include:
  - Multilayer Perceptron (MLP),
  - Convolutional Neural Network (CNN),
  - Recurrent Neural Networks (RNN),
  - Graph Neural Networks (GNN), and
  - Bayesian Neural Network (BNN).
- Extensive **testing** on datasets like **MNIST**, **CIFAR**, **Cora**, etc., has been **performed** and **compared** with PyTorch.

ANN assisted CA Track Finder



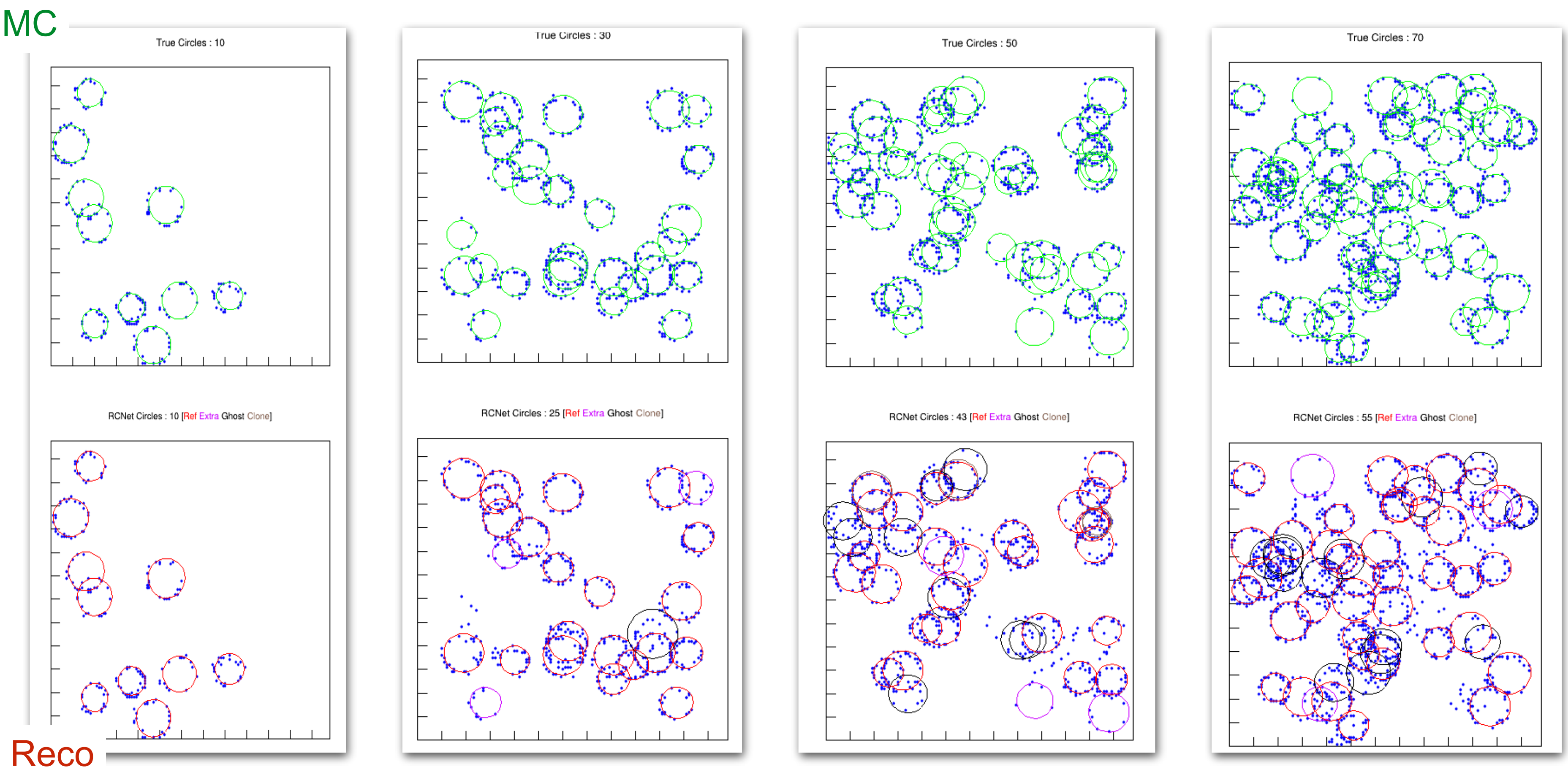
- Kalman Filter (KF) based Cellular Automaton (CA) track finder is extremely good at finding most tracks except low-p secondary tracks. But these tracks are important for physics!
- KF uses the target vertex to fit tracks which makes it lose some secondary tracks.
- Supplement the KF with a neural network which finds triplets from the leftover hits.
- The triplet to track construction phase remains the same.
- A simple Multi-Layer Perceptron (MLP) which takes as input the coordinates of three hits and classifies it as a true or false triplet was implemented into the standalone CA Track Finder.
- Event display shows reconstructed tracks



Reconstructed in **red**, MC in **black**

Future: Replace MLP with a Graph Neural Network (GNN)

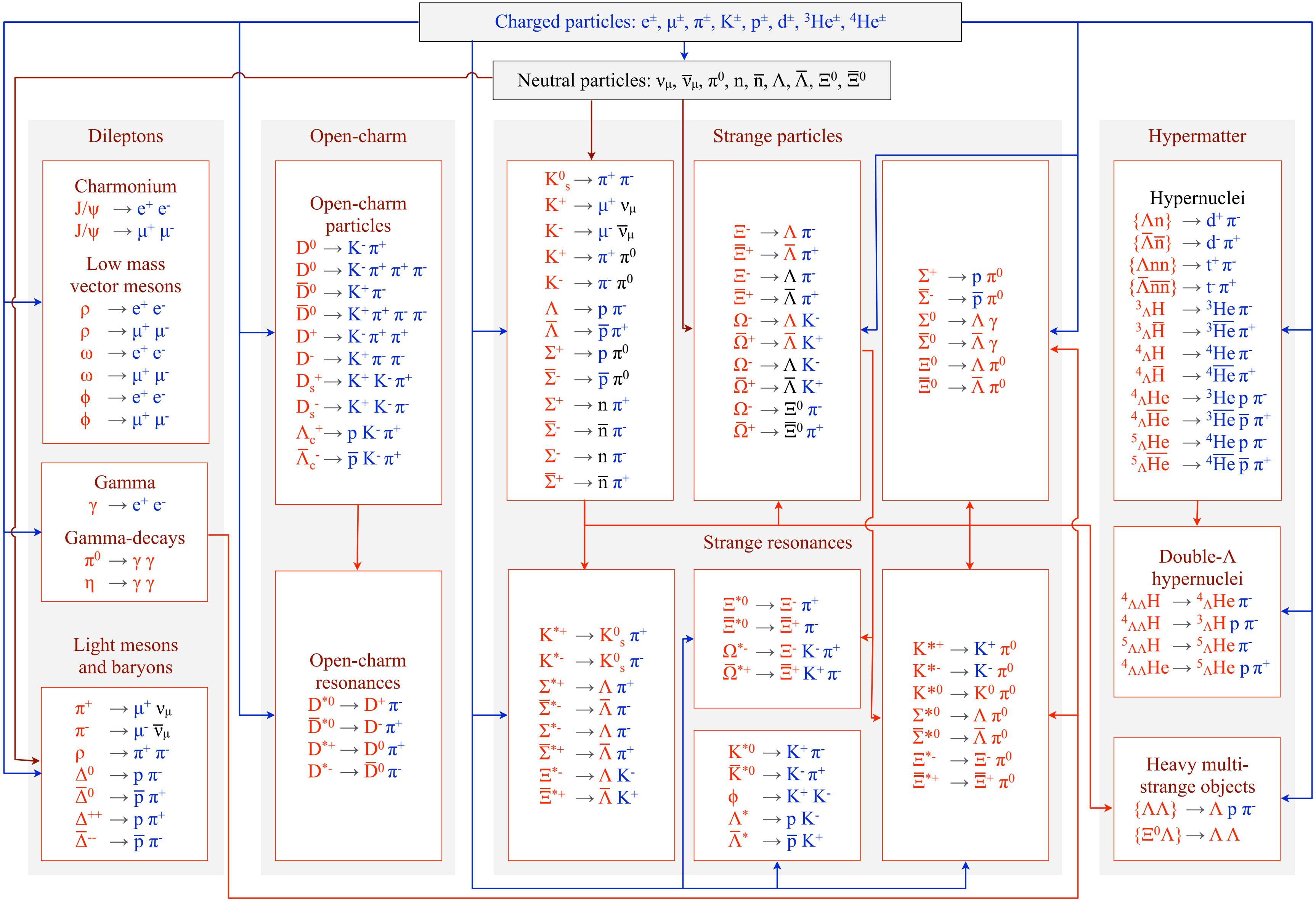
ANN for Ring Finding in RICH High Density Regions



10 Rings *30 Rings* *50 Rings* *70 Rings*

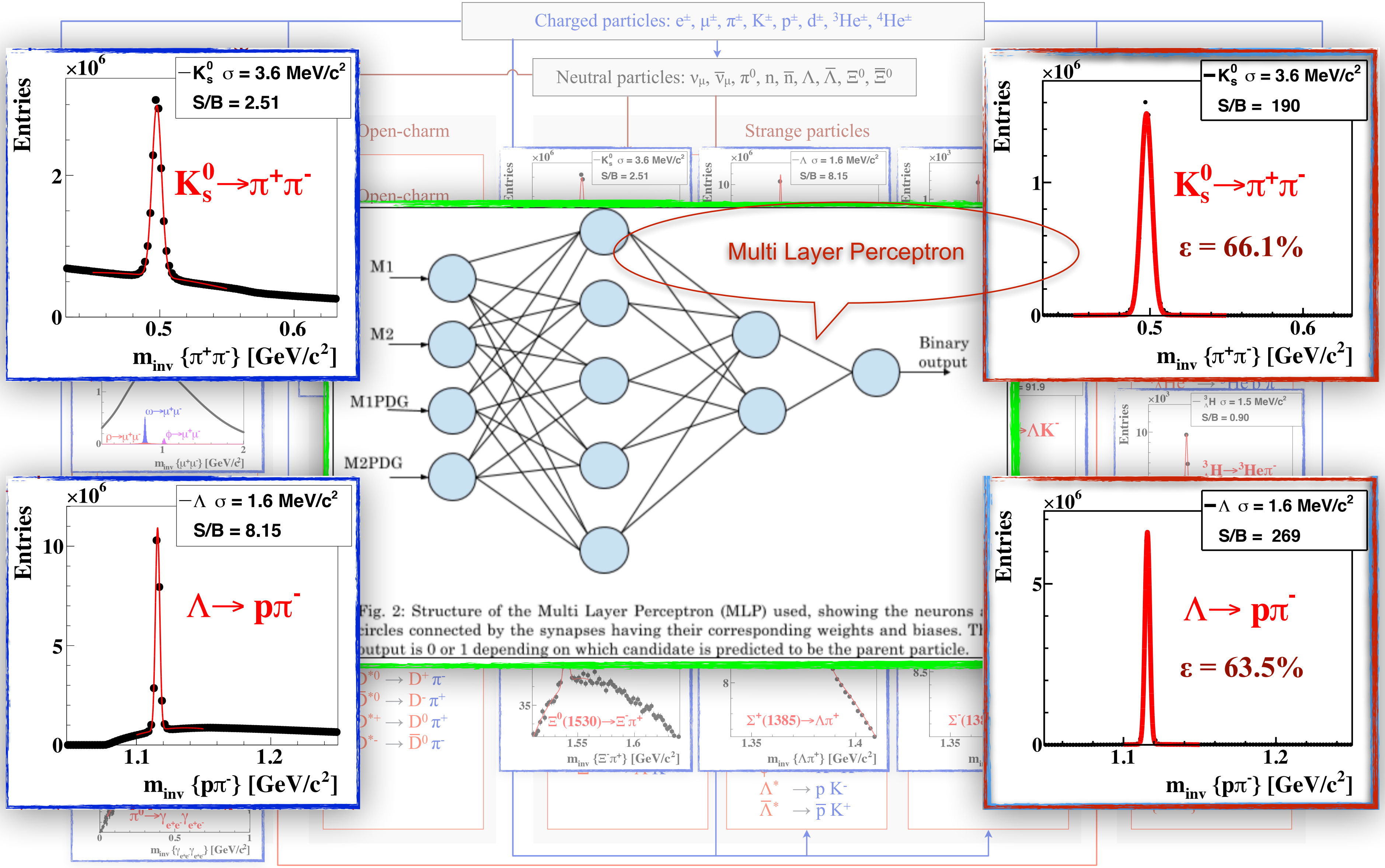
ANN is capable to find rings in high density regions

KF Particle Finder for Online Analysis and Selection



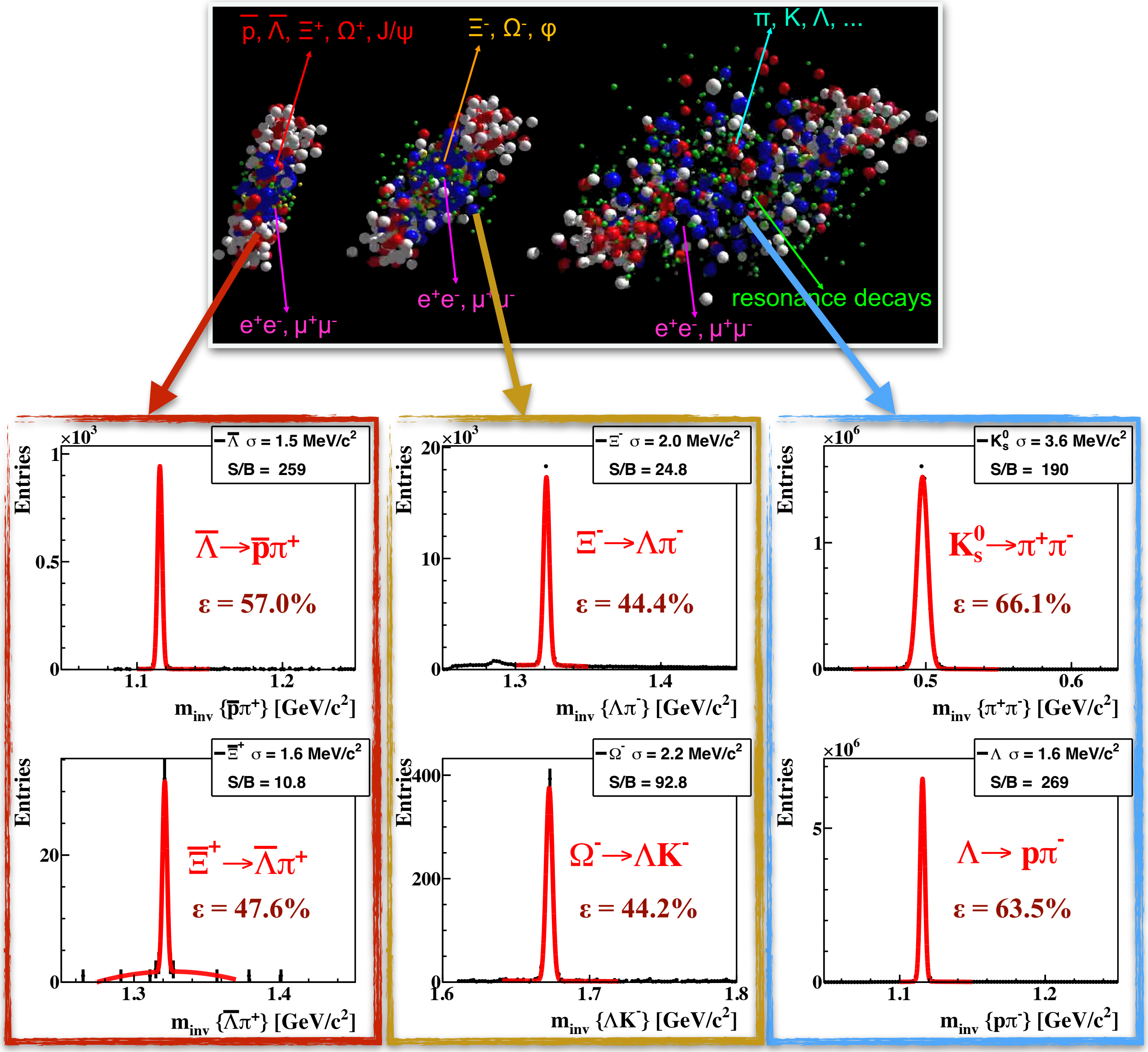
(mbias: 1.4 ms; central: 10.5 ms)/event/core

ANN based Particle Competition in the KF Particle Finder



A Multilayer Perceptron is used to solve the particle competition in KF Particle Finder

Clean Probes of Collision Stages

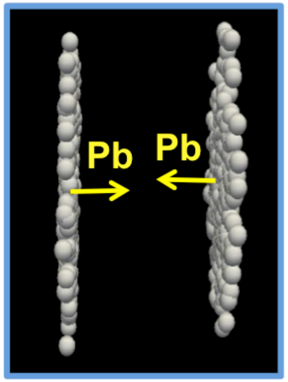


AuAu, 10 AGeV, 3.5M central UrQMD events, MC PID

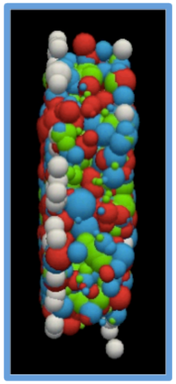
Quark-Gluon Plasma (QGP)

time →

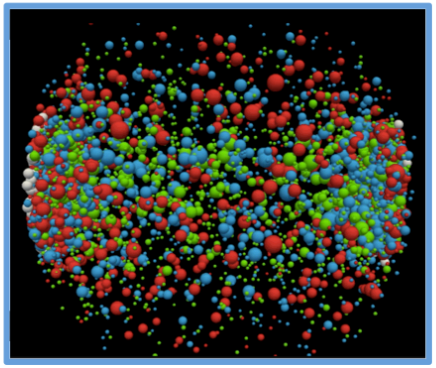
Pre-reaction



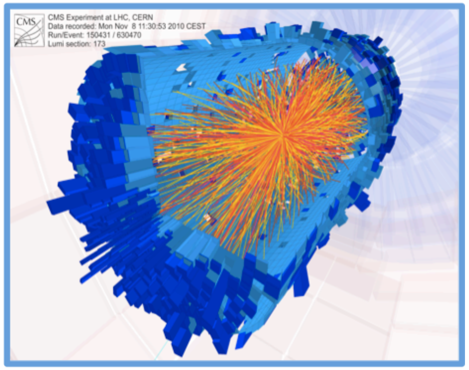
QGP



Hadronization



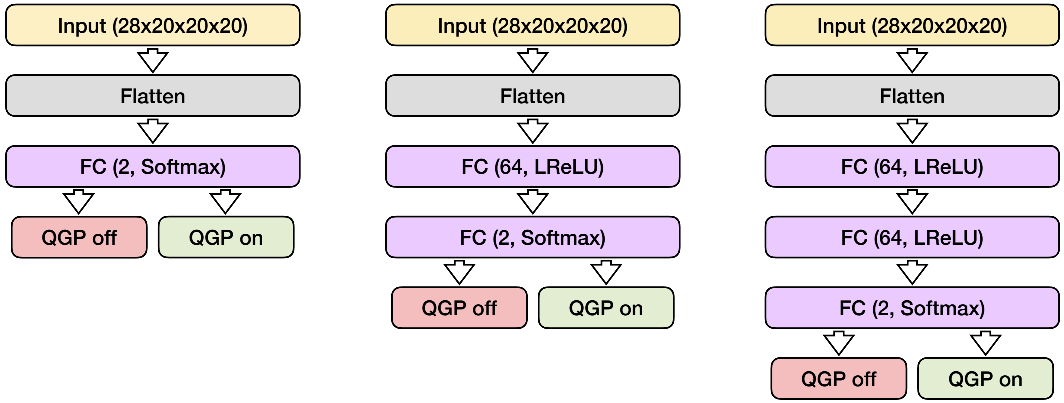
Detection



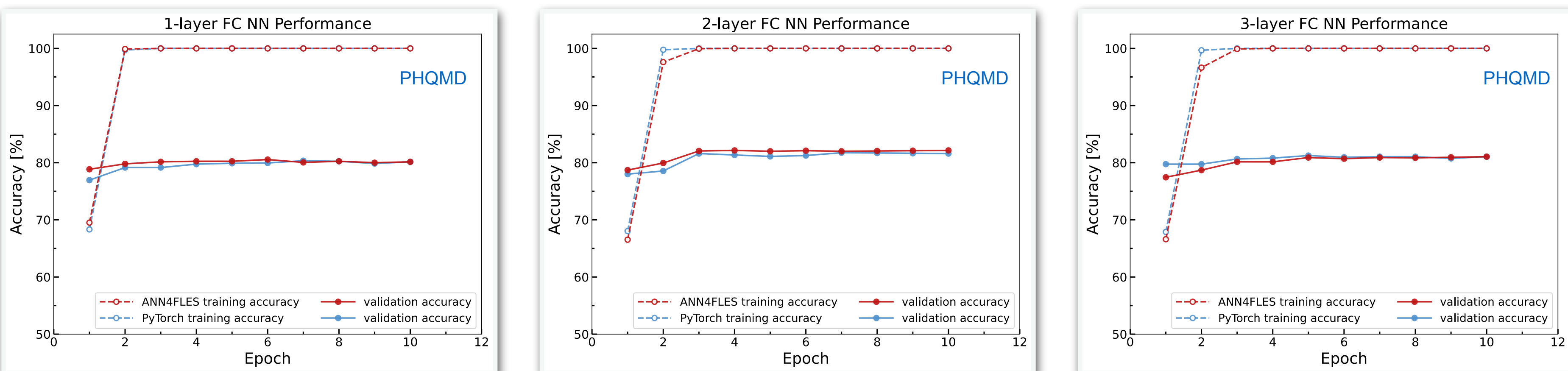
- **Nature of QGP:** A state of matter consisting of deconfined quarks and gluons that exists at extremely high temperatures and densities.
- **Formed in collisions:** Created in heavy ion collisions when nuclei collide at high energies, potentially recreating conditions similar to those just after the Big Bang or at the centers of neutron stars.
- **Study in the CBM experiment:** The CBM experiment aims to study the properties of QGP by observing how it behaves under conditions of high baryonic density.
- **Direct observation of QGP is not possible:** QGP cannot be observed directly because of its extremely short lifetime and its rapid transformation into hadronic matter. Conclusions about its properties are drawn from indirect data obtained from post-collision phenomena.
- **Relying on new particles as probes:** To study QGPs, particles such as mesons and baryons produced in collisions are analyzed. The behavior of these particles provides insight into the characteristics of QGPs.
- **Event classification using the PHQMD model:** Events are classified by analyzing particles generated using the Parton-Hadron Quantum Molecular Dynamics (PHQMD) model. This model simulates the dynamics under extreme conditions and helps to understand the properties and phase transitions of QGPs.

A **QGP Trigger** is important for online selection of interesting collisions

Fully-Connected Neural Networks (FCNN)



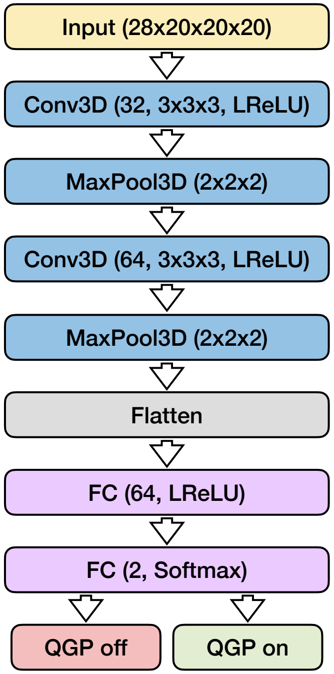
Structure of **one-**, **two-** and **three-layer** Fully-Connected Neural Networks used for QGP detection

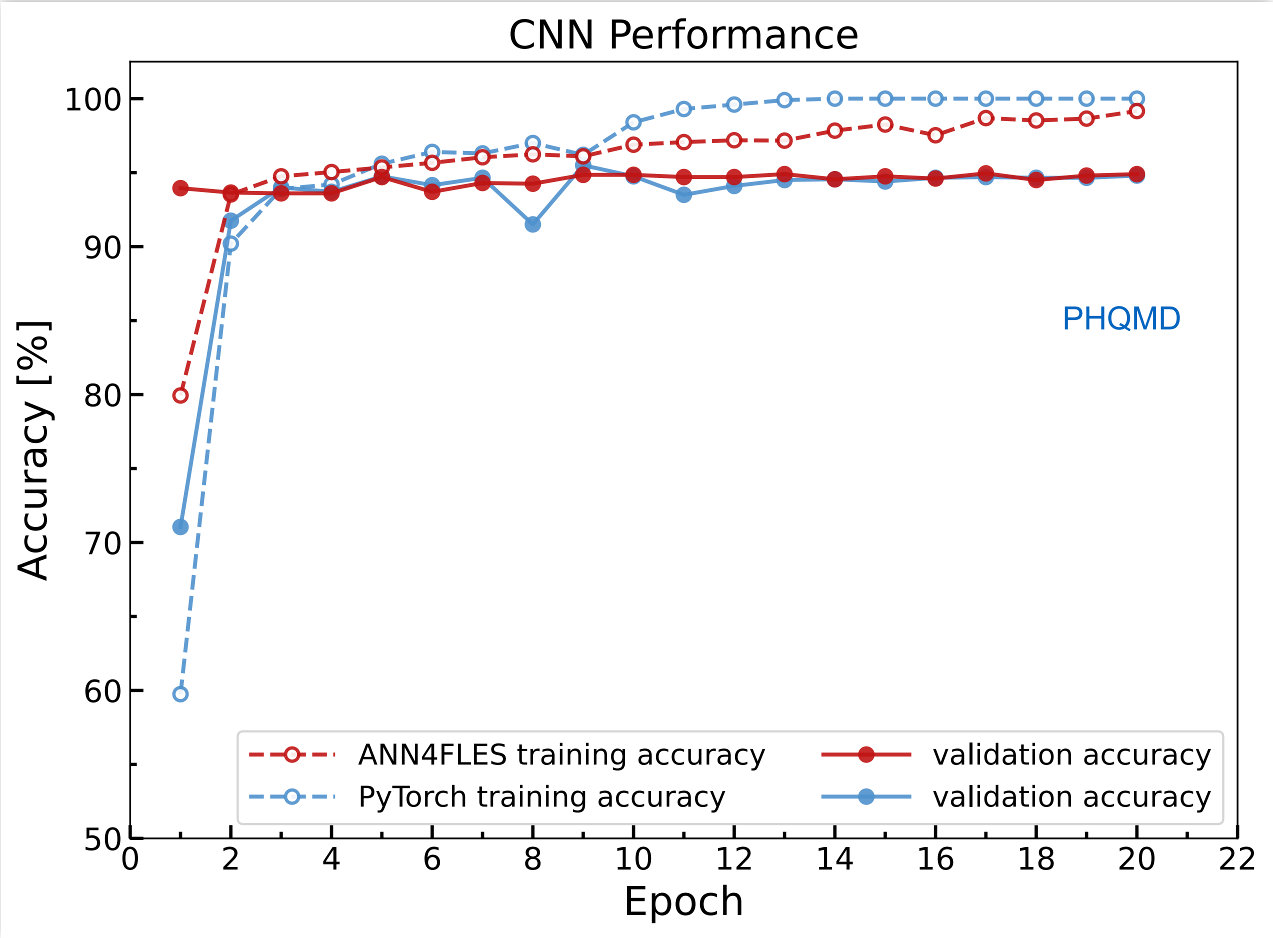


Training and validation accuracy for the **FCNN** networks

A Fully-Connected Neural Network (**FCNN**) based **QGP Trigger** is **not feasible**

Convolutional Neural Network (CNN)





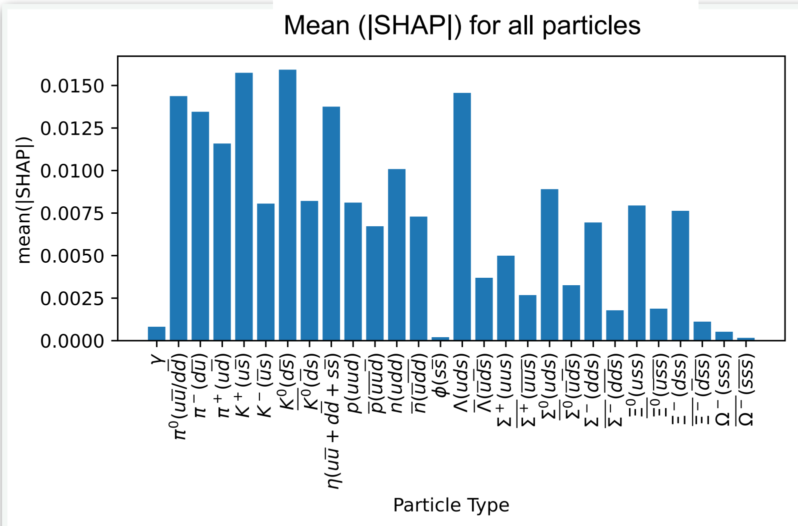
Training and **validation** accuracy for the **CNN**

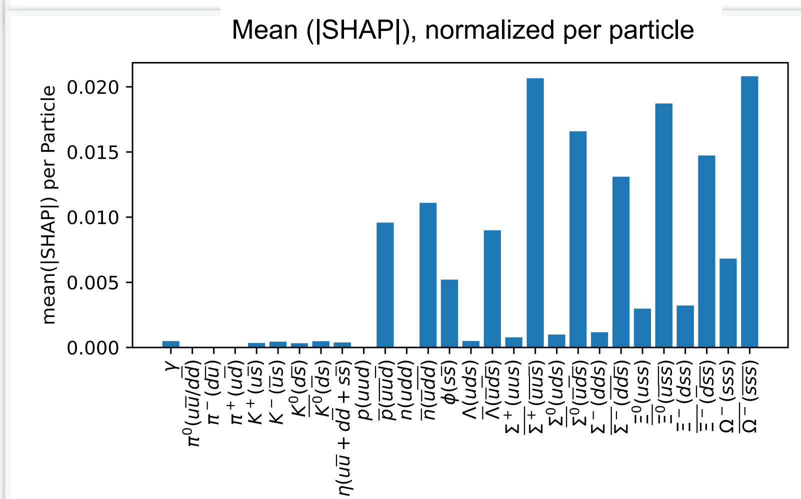
A Convolutional Neural Network (**CNN**) based **QGP Trigger** is **feasible**

Interpretable ANN: Shapley Additive Explanations

Method based on cooperative game theory used to increase transparency and interpretability of machine learning models.

For each feature, SHAP score is determined by evaluating the average contribution of adding the feature over all possible feature subsets defined without that feature.





- **Light particles are important** for model prediction
- **Anti-baryons more important** than baryons per particle

From theory we expect **QGP formation** to involve

- more **strange quarks**
- more **anti-baryons than baryons**

SHAP analysis reveals that ANN has learned the correct characteristics associated with QGP production

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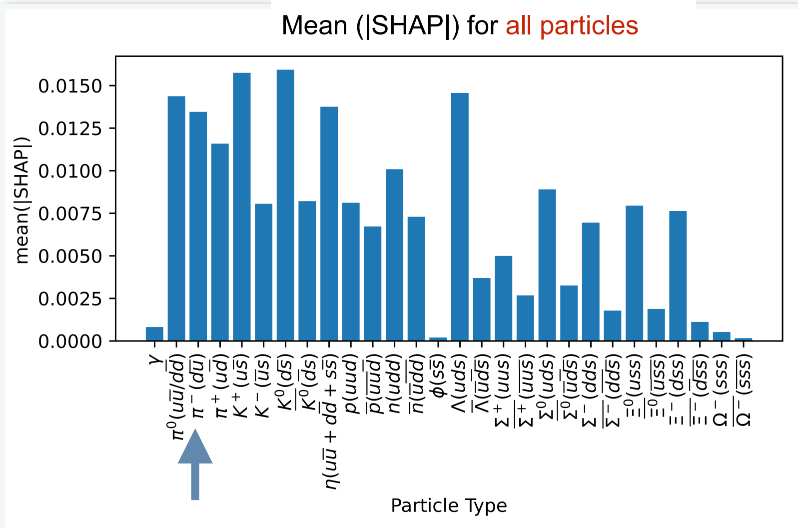

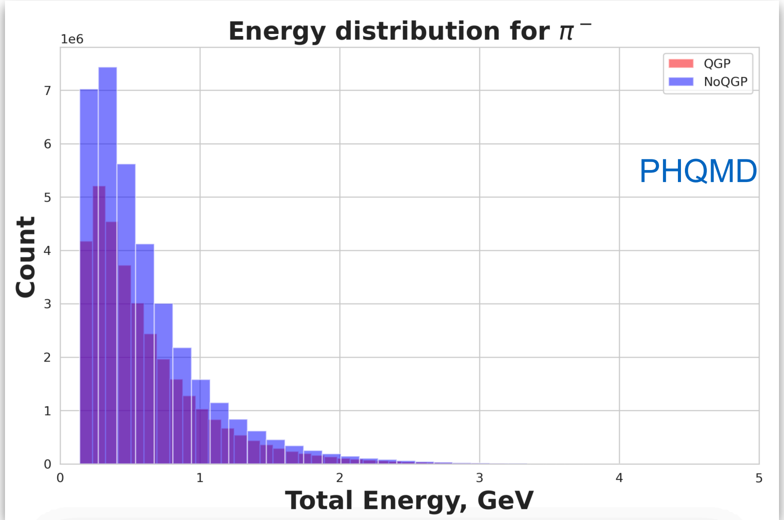

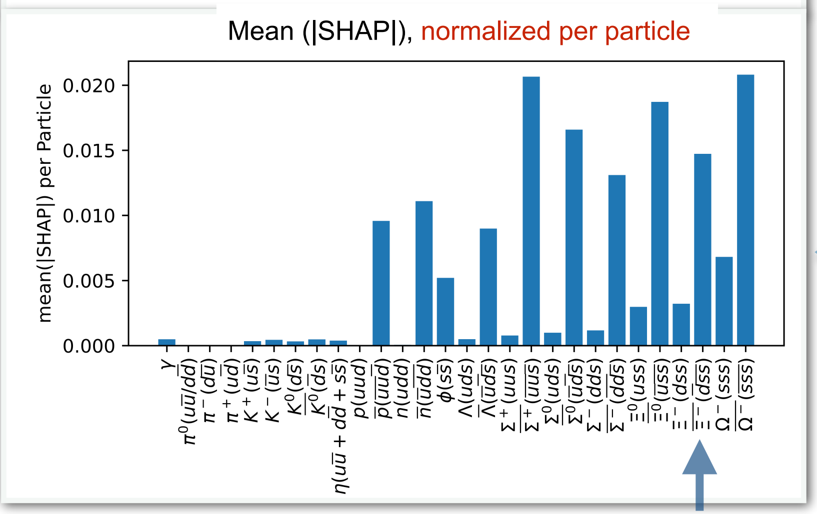

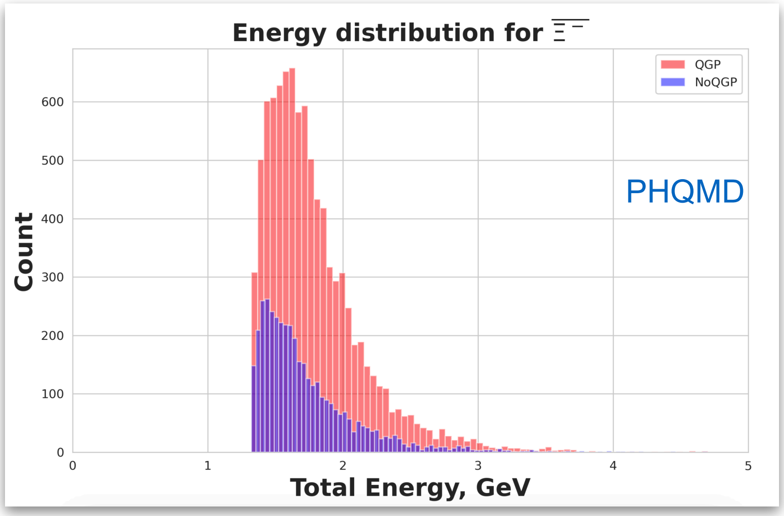

SHAP analysis reveals that ANN has learned the correct characteristics associated with QGP production

Summary

- A C++ package of Artificial Neural Networks for the First Level Event Selection (ANN4FLES) was created for the CBM experiment.
- All networks implemented in the package have been successfully tested on a number of standard datasets and show comparable results to the PyTorch library.
- The ANN4FLES package is now being investigated for various reconstruction and analysis tasks in the CBM FLES package.
- The implementation of a Quark-Gluon Plasma (QGP) trigger based on a Convolutional Neural Network (CNN) is feasible.
- The behavior and results of ANNs can be interpreted more transparently using Shapley's additive explanations, a method that assigns each input feature a value representing its contribution to the final prediction, thereby clarifying how different features influence the model's decisions.