

# Electron Identification using Machine Learning in the MPD Experiment at NICA

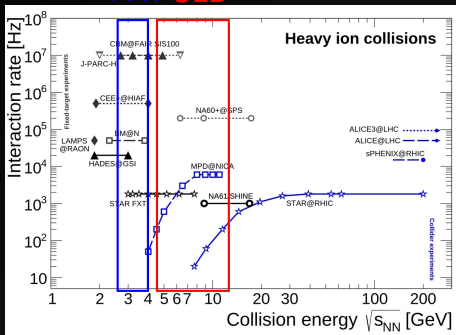
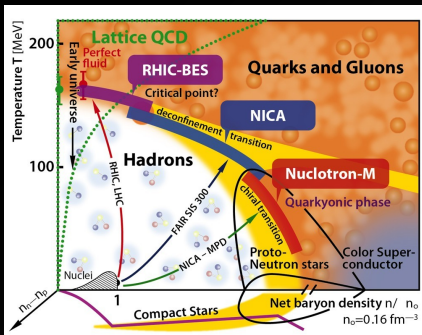
Sudhir Pandurang Rode for the MPD Collaboration

Joint Institute for Nuclear Research

September 15-20, 2025

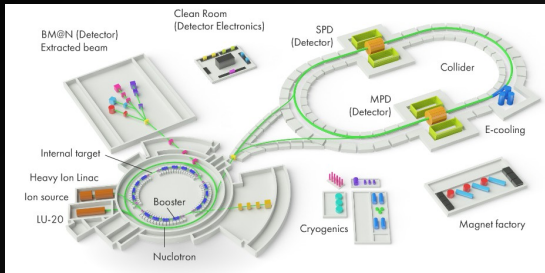
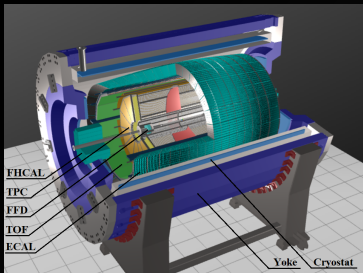
# Heavy-ion collisions

FXT CLD Nucl. Phys. A982 (2019) 163-169



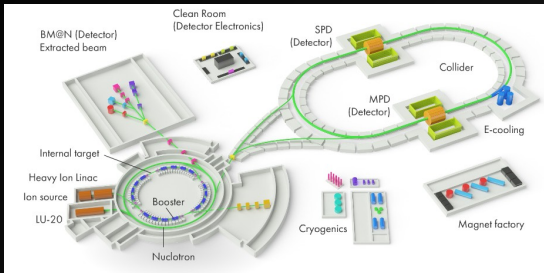
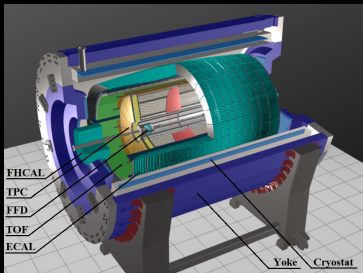
- ▶ Smooth crossover at  $\mu_B \approx 0 \leftarrow$  Early universe like conditions.
- ▶ Explore high  $\mu_B$  matter  $\rightarrow$  Critical end point and 1st order phase transition.
- ▶ Similar net baryon density expected as in the core of neutron stars.
- ▶ MPD and BM@N  $\rightarrow$  QCD matter study at these densities.
- ▶ Various experiments, such as NA61/Shine, STAR-BES and CBM in similar beam energy range.

# Multi-Purpose Detector (MPD) experiment at NICA



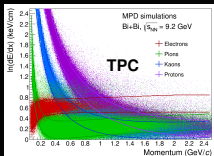
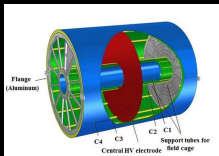
- ▶ Nuclotron-based Ion Collider fAcility (NICA) is a megascience project approaching its full commissioning.
- ▶ MPD is a flagship experiment at NICA: starting operations in 2026.
- ▶ Modes of operation:
  - ▶ Collider mode: two beams,  $\sqrt{s_{NN}} = 4\text{-}11 \text{ GeV} \rightarrow \text{Xe}+\text{Xe}/\text{Bi}+\text{Bi}$  at  $\sqrt{s_{NN}} \approx 7 \text{ GeV}$ ,  $\approx 50 \text{ Hz}$  at start-up
  - ▶ Fixed-target mode: one beam + thin wire ( $50 \mu\text{m}$ ),  $\sqrt{s_{NN}} = 2.4\text{-}3.5 \text{ GeV} \rightarrow \text{Xe}/\text{Bi}+\text{W}/\text{Au}$  at  $\sqrt{s_{NN}} \approx 3 \text{ GeV}$ ,  $\approx \text{kHz}$  at start-up

# Multi-Purpose Detector (MPD) experiment at NICA



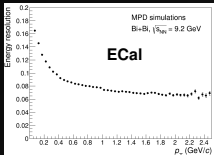
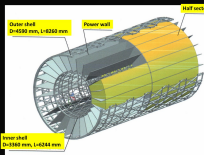
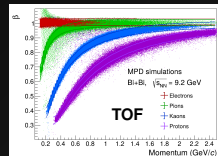
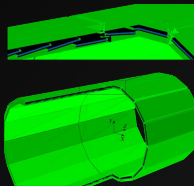
- ▶ Strategy: High luminosity scans in energy and system size to measure different signals.
- ▶ Advantages: Same apparatus for scans with benefits of collider geometry.
  - ▶ maximum phase space, correlated systematic effects for different systems and energies.
- ▶ Sub-systems with modern technologies: TPC, TOF, ECal, FFD, FHCAL.
- ▶ Suitable for dilepton measurements:  $e^+e^-$  pairs.

# MPD sub-systems



- ▶ All 28 (100%) TOF modules are assembled, tested, stored and ready for installation and Spare modules in production.
- ▶ Designed Time and coordinate resolution of  $\approx 80$  ps and  $\approx 0.5$  cm, respectively.
- ▶ Better PID performance is achieved when combined with TPC.

- ▶ 3D tracking with  $dE/dx$  measurement (accuracy of 6-7%) and 1-3% momentum resolution.
- ▶ 24+ ROC and 100+ % FE cards ready.
- ▶ HV/leakage tests – ongoing
- ▶ TPC + ECAL cooling systems under commissioning



- ▶ Full configuration: 50 half-sectors in full azimuth (25 full sectors).
- ▶ Measures deposited energy from 10 MeV to a few GeV with resolution of about 7% at 1 GeV.
- ▶ 45 half-sectors to be ready by October, the rest depends on WLS fiber supply

**Ready for commissioning by end of the year.**

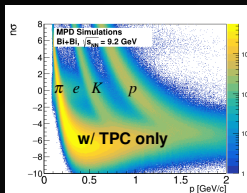
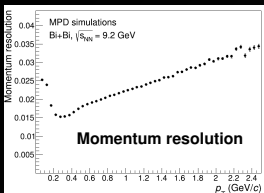
# Particle Identification (PID) in Heavy-Ion Experiment

- ▶ PID is a crucial step in the physics analysis of the experimental data.
- ▶ It enables detailed study of the produced identified particles, their spectra, and yields.
- ▶ PID helps explore different phenomena such as, chemical equilibrium, strangeness enhancement, and collective flow of various species.
- ▶ It allows disentangling complex particle production mechanisms.

**Such a crucial step requires excellent detector performance!**

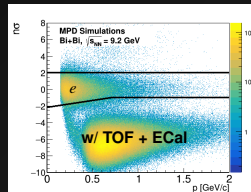
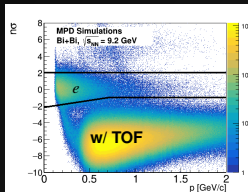
# Track reconstruction and Particle Identification (PID)

- ▶ MPD has excellent track reconstruction and particle identification capabilities.



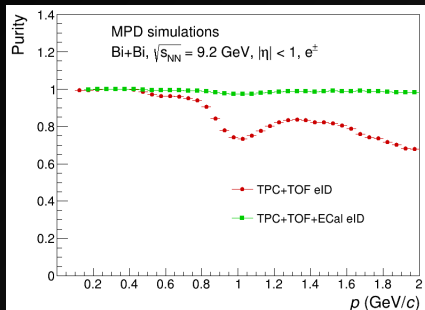
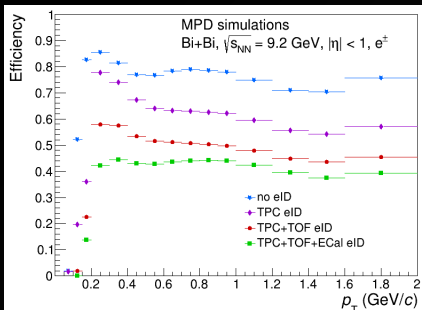
- ▶ TPC measures  $\langle dE/dX \rangle$  and momentum with resolution of about 6-7% and 1-3%, respectively.

- ▶ TPC alone is not enough to achieve pure electron sample.
- ▶ TOF complements with purity about 80% beyond  $p = 1$  GeV/c.
- ▶ Addition of ECal allow even better electron-hadron separation.



**The purity improves significantly with ECal!**

# Electron reconstruction efficiency and Purity



- ▶ With TOF, the purity reaches about 80% and the efficiency of about 50% is achieved.
- ▶ The purity can reach up to 100% with the help of ECal along with nearly 45% efficiency: exceptional electron-hadron separation above  $p \gtrsim 0.8$  GeV/c.

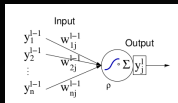
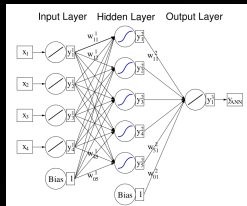
**Still, the loss of efficiency using traditional cuts method is significant! → need a better way to improve this.**



# PID using Machine Learning

- ▶ Machine learning has been used for the identification of various particles for some time now.
- ▶ This approach can help in improving the electron identification efficiency → S/B and significance in dielectron analysis.
- ▶ Procedure:
  - ▶ Preparation of the data sample, generally, two samples, one for training (50%) and other is for validation (50%) → Actual proportion of Signal (electrons) and Background (hadrons).
  - ▶ Selection of the discriminating variables.
  - ▶ Training model on the sample and validation with testing sample.
- ▶ There are many models/classifiers available in TMVA package which used in this study → for instance, Multi-Layer Perceptron (MLP) and Boosted Decision Tree (BDT).
- ▶ Only studies with MLP and BDT are shown in this presentation.

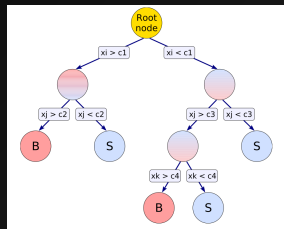
# Neural Network and Decision Tree<sup>1</sup>



► **MLP:** Neurons that learn patterns in data, organized in layers with direct connections from one layer to the next.

- Neuron response functions map inputs to outputs.
- Good at finding complex patterns in data.
- Needs lots of trial-and-error to set up properly

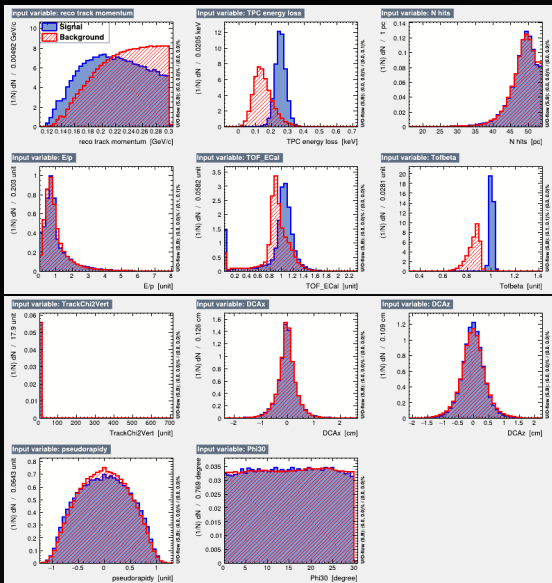
- **BDT:** Simple model making predictions via step-by-step "if-then" rules
- Turns weak trees into strong predictors through sequential error correction
- Robust performance on structured data
- Training speed scales with number of trees



- Classification between signal and background is carried out by training models to learn a decision boundary based on discriminating variables.

<sup>1</sup> **Disclaimer:** I am not an expert on Machine Learning. This is just for information.

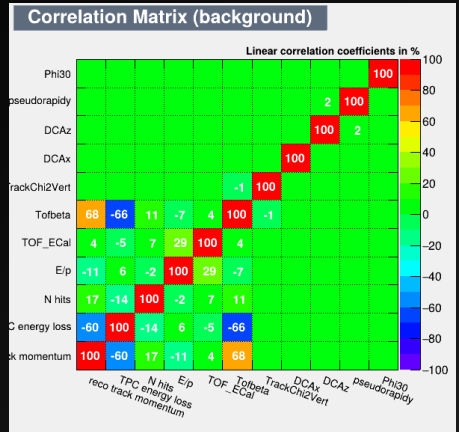
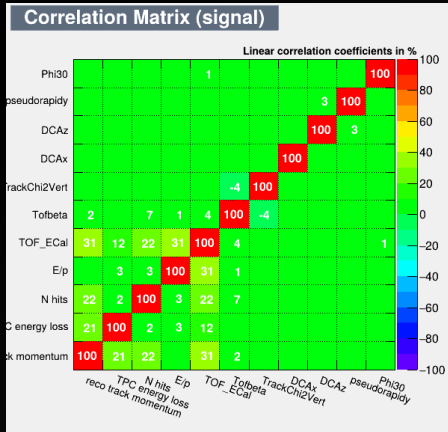
# Input variables



Following discriminant variables are fed to the ML models:

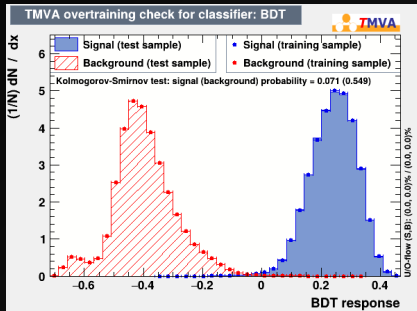
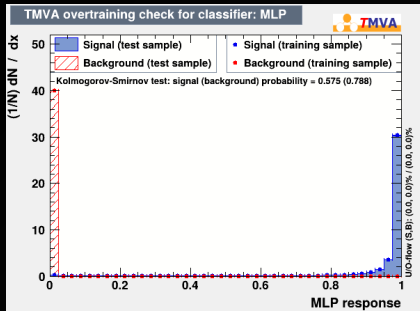
- ▶ Momentum
- ▶ dEdX
- ▶ No of Hits
- ▶ E/p
- ▶ Velocity,  $\beta$  measured in the TOF and ECal
- ▶ Track chi2 to vertex
- ▶ DCAx
- ▶ DCAz
- ▶ Pseudorapidity ( $\eta$ )
- ▶ Azimuthal angle ( $\phi$ )

# Correlation matrices: $e^\pm$ (Signal) and hadrons (Bkg)



- ▶ Almost all variables for signal are uncorrelated.
- ▶ In case of background, there is (anti-)correlation between some variables, for instance, dEdx and Tofbeta.

# Momentum integrated training

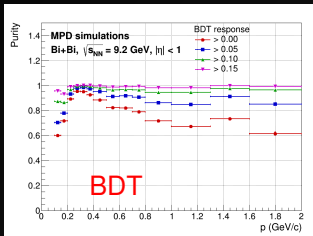
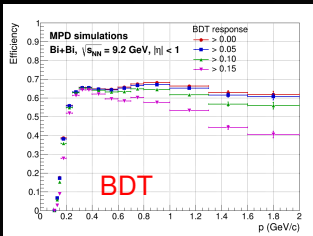


- ▶ The training was performed well.
- ▶ Overtraining test carried out using Kolmogorov Smirnov test<sup>2</sup> → suggested no overtraining.

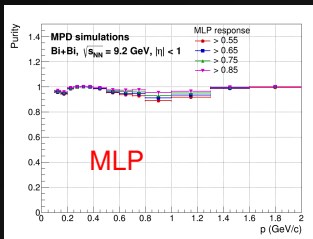
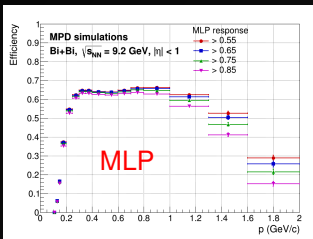
<sup>2</sup>provides a  $p$ -value equal to the statistical probability that two samples are drawn from the same distribution. The smaller the  $p$ , the greater the overtraining. As a rule of thumb, it is recommended to try to reduce overtraining if  $p < 0.01$ , especially if the separation is visibly poorer for the testing samples than for the training samples.

# Momentum integrated training

- Both BDT and MLP are not able to perform better at high momenta.

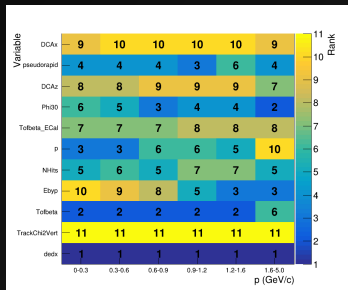
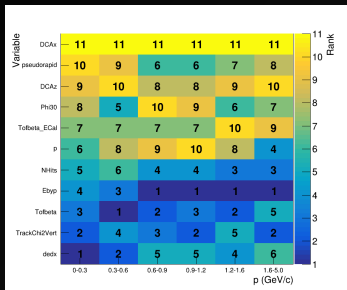
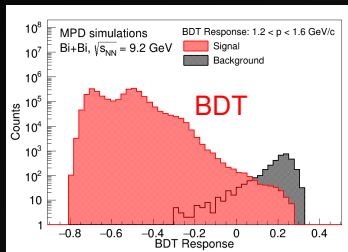
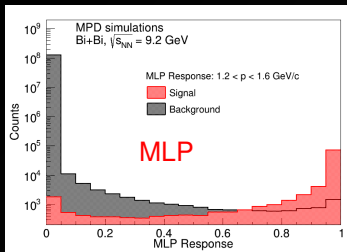


- Efficiency drops at high momenta.



**Momentum differential training may improve the classification at high momentum.**

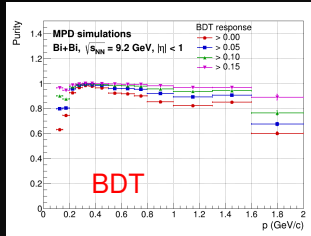
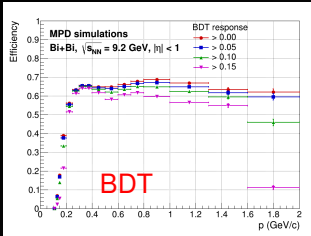
# Momentum differential training



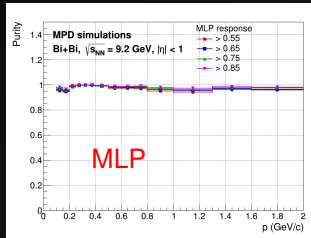
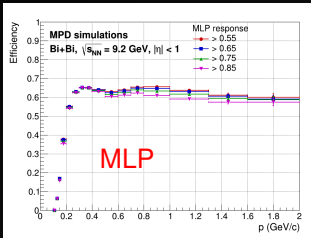
- Samples were trained in various momentum intervals.
- Classifier-dependent sensitivity to input variables at higher momenta.

# Momentum differential training

- ▶ BDT still seems to be less effective at high momenta compared to MLP.



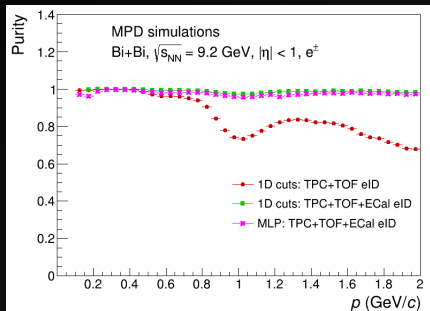
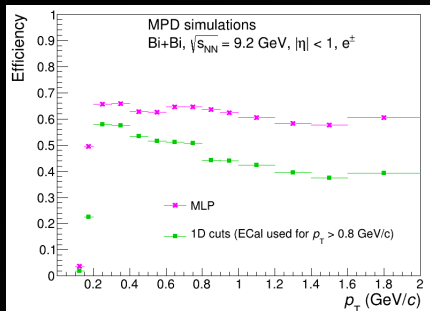
- ▶ MLP perform better and provide p-independent efficiency and purity.



**Momentum differential training helps to separate signal and background effectively, especially, using MLP.**



# Benefit of Machine learning in PID



- ▶ Efficiency obtained using neural network i.e. Multi-layer Perceptrons (MLP) shows enhancement in the electron identification performance of the MPD compare traditional 1D selection cuts method.
- ▶ Purity has remained almost 100% as in traditional method.
- ▶ Black-box nature pose challenges for debugging, Inherit biases from training data, and Systematic uncertainties are harder to quantify.

**Efficiency is improved by 50% above  $p_T > 0.8$  GeV/c!**

# Conclusions

- ▶ All MPD sub-systems are in advanced stage and ready for commissioning by end of the year → MPD is expected to begin operations in 2026.
- ▶ Particle Identification is an important step in the various physics analyses.
- ▶ ECal provides excellent electron-hadron separation: leads to highly pure electron sample.
- ▶ Electron Identification efficiency suffers loss due to traditional cut based method.
- ▶ Improvement in the electron identification performance is observed using Machine Learning.
- ▶ Both MLP and BDT does enhance the efficiency, however, MLP performs better in the high momentum region.

**THANK YOU**

# BACK-UP

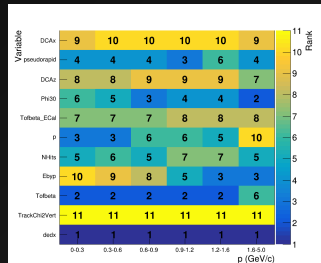
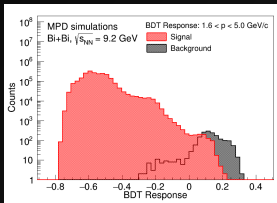
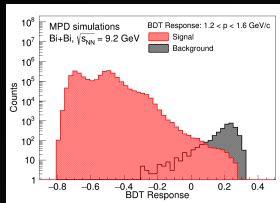
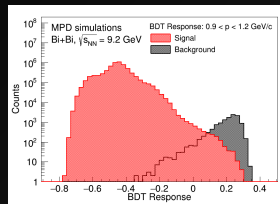
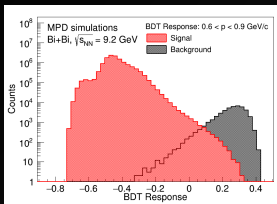
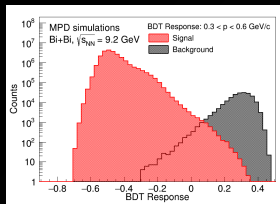
# Forward detectors



- ▶ FFD (Fast Forward Cherenkov Detector): Provides fast triggering of A+A collisions and generates the start-time ( $T_0$ ) pulse generation for the ToF detector with a time resolution better than 50 ps.
- ▶ Two FFD detectors at  $2.7 < |\eta| < 4.1$
- ▶ FHCAL (Forward Hadron Calorimeter): Event centrality and reaction plane measurements with potential for event triggering.
- ▶ Two FHCAL detectors at  $2 < |\eta| < 5$ ,  $\approx 1 \times 1 \text{ m}^2$  each

**Ready for installation**

# Momentum dependent training (BDT)



# Momentum dependent training (MLP)

