# Particle Identification Algorithms Based on Machine Learning for STCF

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## Introduction

*** The Super Tau Charm Facility (STCF):**

- **STCF** is the next generation positron-electron collider in China, designed specifically to explore various physics phenomena in the $\tau$-charm energy region.


Schematic layout of the STCF detector concept.

**Parameters of STCF**

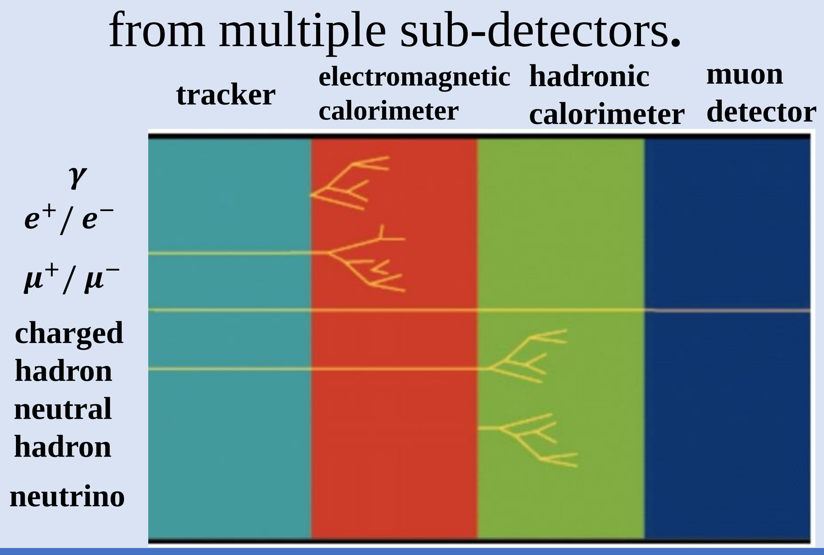
- $E_{cm}$ = 2-7 GeV
- L = 0.5×$10^{35}$ $cm^{-2}$ $s^{-1}$
- Circumference: Double-ring, 600-800 m
- Crossing angle: 2×30mrad

**Physics Objectives**

- Rich physics with c quark and $\tau$ leptons
- Studying flavor physics and CP violation physics
- Non-perturbed strong interaction and new exotic hadronic states
- Searching for new physics

*** Particle identification (PID):**

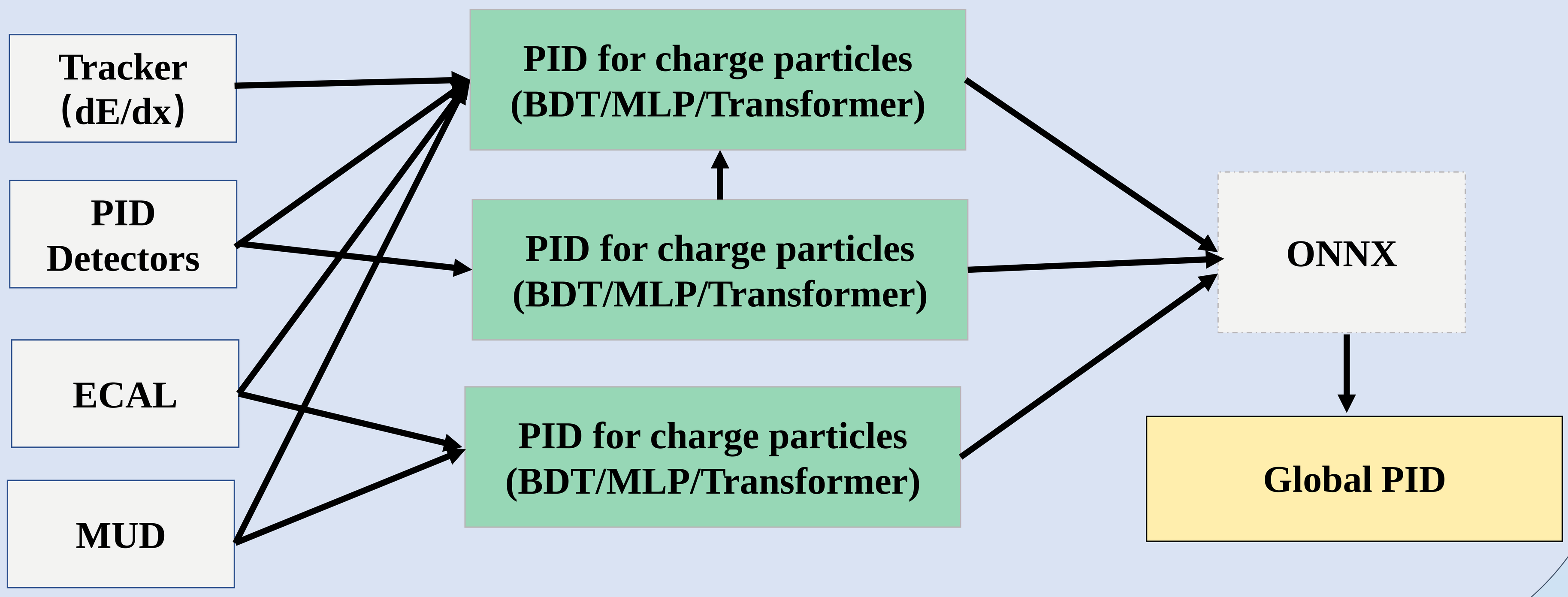
- **Particle identification (PID)** is one of the most important and commonly used tools for the physics analysis in STCF.
- The PID algorithm performance is crutial for exploiting the potential of STCF detectors.
- Better particle identification usually requires the combination of information from multiple sub-detectors.




- *$\pi$/K (K/p) 3-4$\sigma$ separation up to 2Gev/c*
- *$\mu/\pi$ up to 2Gev/c, $\pi$ suppression ~ 3%*
- *Good discrimination power for $\gamma/n/K_L^0$*

*** Particle Identification Algorithms Based on Machine Learning :**

- The data-driven **machine learning (ML)** approach has opened up new avenues for improving PID performance, with strong modeling and generalization capabilities.
- ML excels at integrating information from all sub-detectors and performing "intelligent fusion" of trajectory information.
- Innovated and developed a Global Particle Identification (GlobalPID) software algorithm based on the ML techniques.
  - Identification for charged particles (e/μ/π/K/p) :Taking BDT (based on XGBoost) as a baseline model
  - Particle identification of hadrons based on Convolutional Neural Networks (CNN).
  - Neutral particle($\gamma/K_L^0$/n) identification based on CNN.



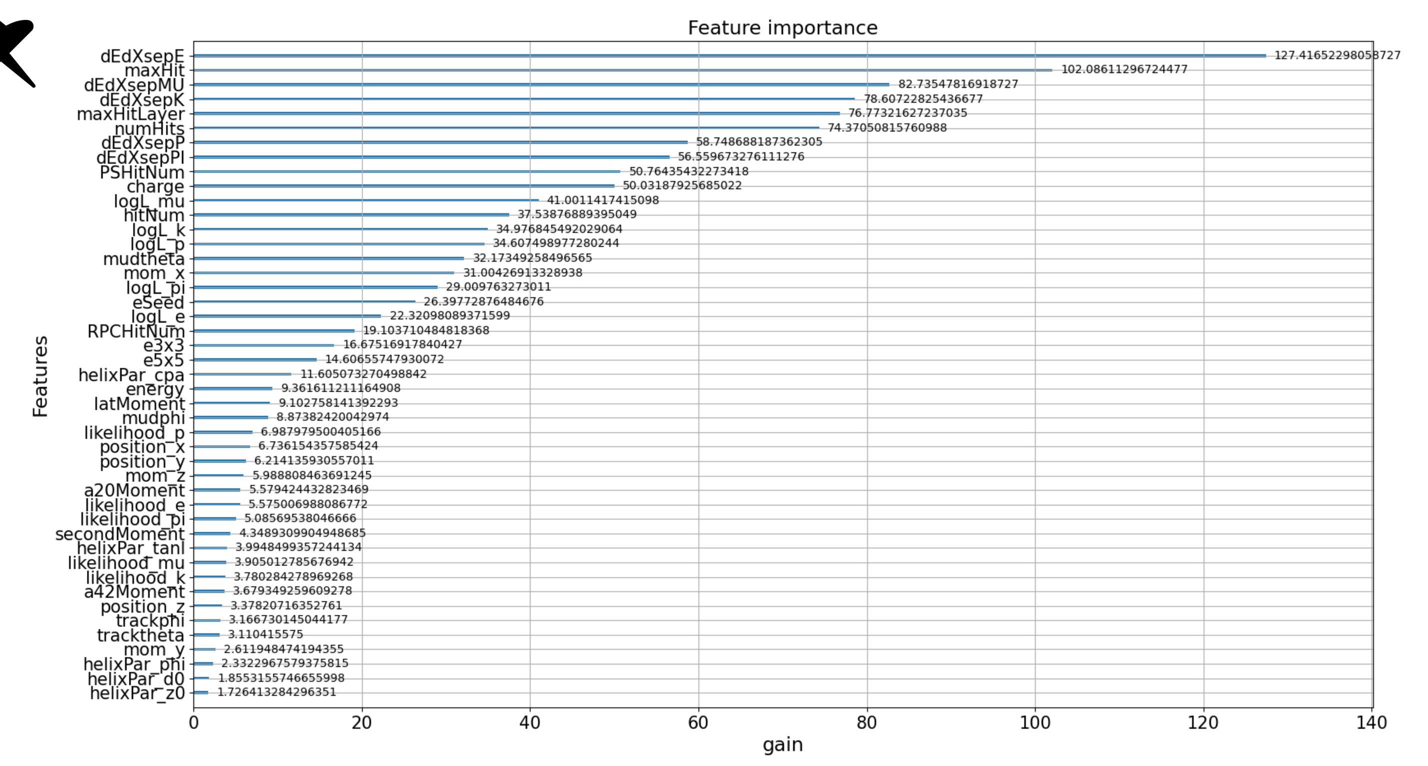

## Identification for charged particles

*** Data Sample:**

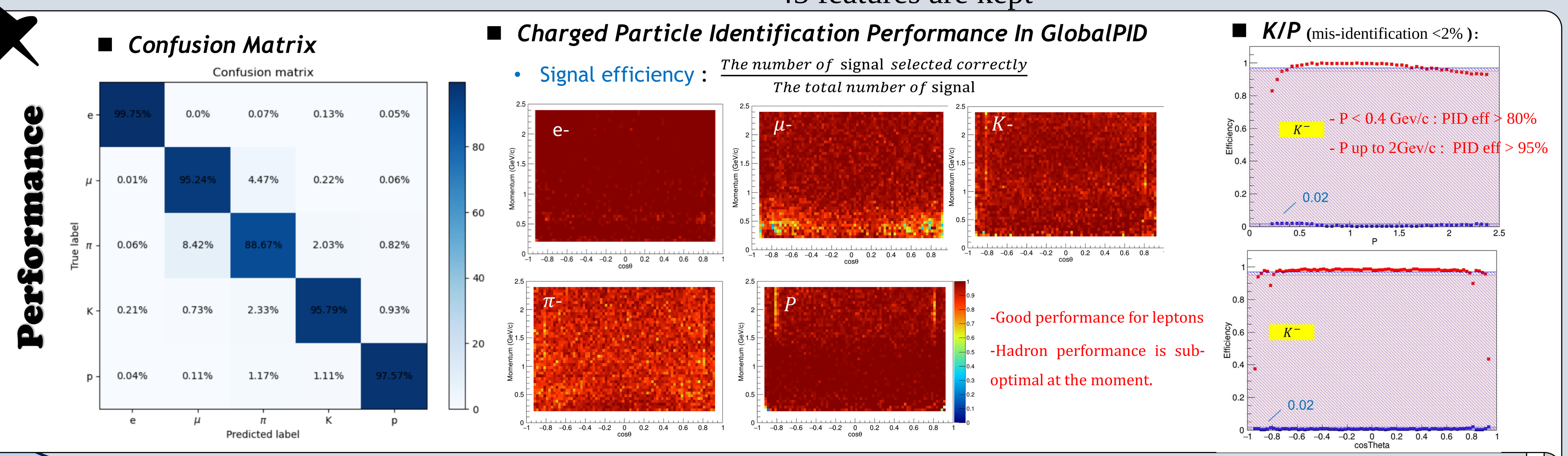
- Selecting a subset of the most informative features from large amount of interrelated sub-detectors information can help stabilize the model training process
  - MC single charged track using ParticleGun
  - 50000 tracks for each type (e±, μ±, π±, K±, p±)
  - p∈(0.2, 2.4 )Gev/c, $\theta$∈(0°, 180°), phi ∈(0°, 360°)
  - Pre-processing: Flatten momentum and θ spectrum to avoid bias due to p/θ distribution
  - 45 features are kept

*** Training and Tuning:**

- Target: automated optimization of BDT hyperparameters
  - Reduce manual intervention and time costs
  - Improve model efficiency and reliability
- Optimal hyperparameters are obtained based on GridSearchCV
- Selected hyperparameters
  - max_depth: 7
  - n_estimators: 800




**Performance**




## Neutral particle identification

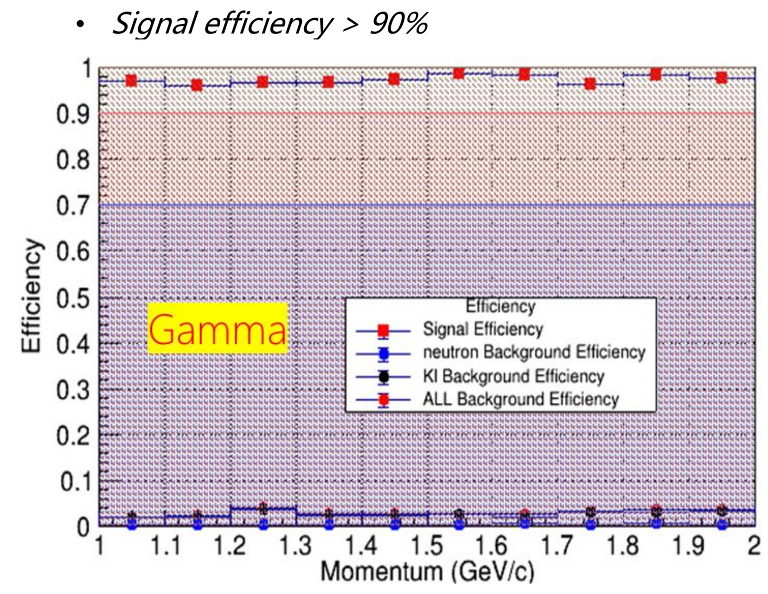
*** Neutral particle identification needs to consider the energy deposition, time response and MUD hitting information of ECAL**

- The energy deposition information of the electromagnetic calorimeter is projected onto a two-dimensional plane
- The MUD hitting information is used as additional input
- CNN is used for image classification
- Neutral Particle Data Sample：
  - $\gamma/K_L$/n
  - Generated by ParticleGun
  - 100,000(Each type)
  - P ∈ （0，2.0）Gev/c,$\theta$ = 90°,$\varphi$ = 0°

***The initial implementation of a global neutral particle discriminator based on CNN**

**Performance**

- **Gamma**:
  - *Good photon discrimination performance*
  - *Signal efficiency > 90%*




## GlobalPID package

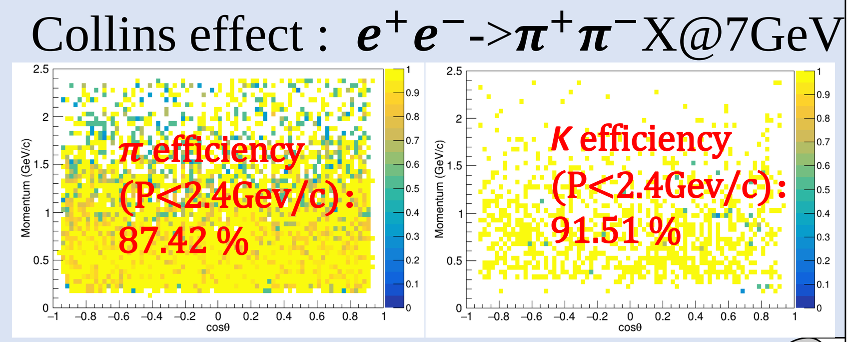
*** The BDT model and GlobalPID algorithm have been integrated into the OSCAR software for analysis and research purposes**

*** Physical analysis and verification**

- $J/\varphi \rightarrow \rho\pi^0 \rightarrow \pi^+\pi^-\gamma\gamma$(Exclusive MC)

| Selection criteria | Efficiency |
| --- | --- |
| The positively charged track is identified as pion | 88.70% |
| The negatively charged track is identified as pion | 88.10% |
| Both tracks are identified as pion | 78.02% |

- Collins effect： $e^+e^-\text{->}\pi^+\pi^-X$@7GeV




### Get Started with Analysis in OSCAR

Therefore, in the STCF experiment, we have developed a new particle identification software package based on data-driven machine learning methods. The GlobalPIDSvc software package includes pre-trained BDT (based on XGBoost) model and algorithm, and is an important part of the OSCAR software package's Analysis branch.To help analysts become familiar with the software package and its functionalities, the user manual is as follows:

1 Users need to add the directive to include the GlobalPID header file in the source file of the instance selection program.

```
#include "GlobalPID/GlobalPIDSvc.h"
```

2 Users need to check and retrieve the GlobalPIDSvc instance in the initialize() function of the instance selection program.

```
SniperPtr<GlobalPIDSvc> _globalpidsvc(getParent(), "GlobalPIDSvc");
if ( _globalpidsvc.valid() ) {
  LogInfo << "the GlobalPIDSvc instance is retrieved" << std::endl;
}
else{
  LogError << "Failed to get the GlobalPIDSvc instance!" << std::endl;
  return false;
}
m_pid = _globalpidsvc.data();
```

3 To obtain the information of a specific track which needs particle identification as well as the information of each subdetector.

```
m_pid->calculate(RecParticle);
```

4 Users can choose the PID mode, the currently supported PID modes are: All $(e/\mu/\pi/K/p)$, $\pi/K/p$, $\pi/K$, $e/\pi/K$, $\mu/\pi$.

```
m_pid->setmode (m_pid->onlyKaon()|m_pid->onlyPion()|m_pid->onlyProton());
m_pid->setmode (m_pid->onlyPionKaonProton());
```

5 Users can obtain the predicted probabilities of the trajectory under five particle hypotheses.

```
float m_prob_e = m_pid->prob(Electron);
float m_prob_mu = m_pid->prob(Muon);
```

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