Paving the last mile of AI4HEP at BESIII

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BESIII PhD Thesis Awards
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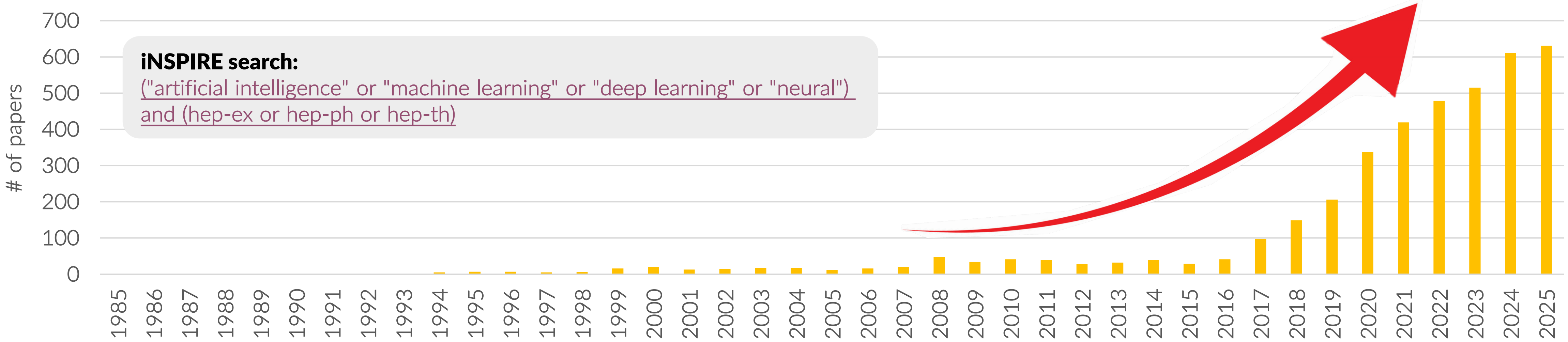
Yes,

◉ **AI / Machine Learning / Deep Learning is reshaping every scientific discipline, including HEP**



HEP experiment: Tevatron & LEP started operation | LHC started operation | LHC Run2

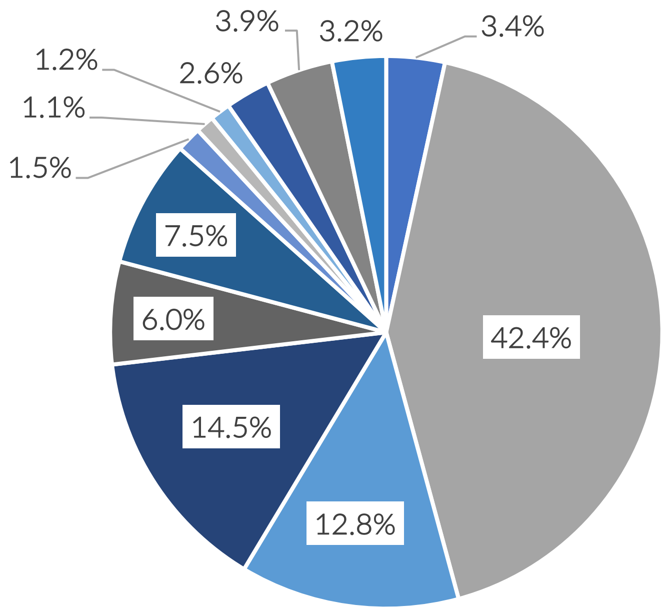
AI method: Back propagation | SVM | Random forest | DBN | AlexNet | GAN ResNet | AlphaGo Transformer | BERT GNN | GPT-3 | LLM Diffusion | ……

"Deep learning era"

- AI4HEP progress is driven by both experimental needs and new computational methods

But...

- **In the modern deep learning era,**
  a substantial gap has emerged between state-of-the-art AI techniques and their practical applications in HEP



https://iml-wg.github.io/HEPML-LivingReview/

- Reviews
- Classification
- Regression
- Generative models
- Anomaly detection
- Simulation-based inference
- Equivariant networks
- Decorrelation methods
- Foundation models, LLMs
- Uncertainty quantification
- Formal theory & ML
- **Experimental results**
  82 out of 2602 papers

- Experimental analyses account for only **~3%** of modern AI4HEP publications
- Multivariate methods (e.g., BDT) still dominate ML applications in HEP experiments,
  which were invented 30 years ago and have only $\frac{1}{1,000} \sim \frac{1}{1,000,000}$ of scale of modern Deep Neural Networks

Why?

- **Many AI methods extend beyond current experimental needs**
  - Not targeting urgent experimental bottlenecks
  - Or being too ambitious for near-term deployment

- **Reliability & robustness of AI methods are concerning**
  - Understanding & controlling the behavior of sophisticated DNNs
  - Ensuring unbiased physics outcomes

- **Shortage of successful, real-world examples**
  - Demonstrating AI's capability in solving concrete physics problems
  - Establishing workflows to address above concerns
  - Gaining acceptance through peer-reviewed results within HEP community

- **...**

Our contributions

- **During my doctorial study, we collaborators developed 3 practical AI methods at BESIII:**
  - Neutral hadron reconstruction
  - Charmed hadron tagging
  - General signal identification

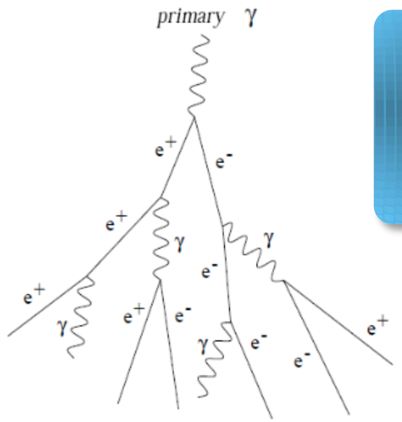
- **These methods enabled several important measurements of charmed hadron decays:**
  - First observation of the semi-leptonic decay $\Lambda_c^+ \to n e^+ \nu_e$
    - BAM-632, Nature Commun. **16**, 681 (2025)
  - First observation of the hadronic weak decay $\Lambda_c^+ \to p\pi^0$
    - BAM-774, Phys. Rev. D **111**, L051101 (2025)
  - Most stringent constraint on the radiative leptonic decay $D^+ \to \gamma e^+ \nu_e$
    - BAM-826, Chin. Phys. C **49**, 083001 (2025)

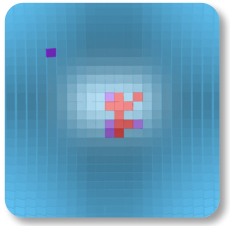
Neutral hadron reconstruction

- **Long-lived neutral hadrons $(n,\ K_L^0)$ are important probes for physics at τ-charm region**
  - Participated in hyperon & charmed hadron decays, light hadron spectrum, exotic states, etc.
  - However, BESIII has no dedicated hadronic calorimeter
  - Detection mainly rely on EMC

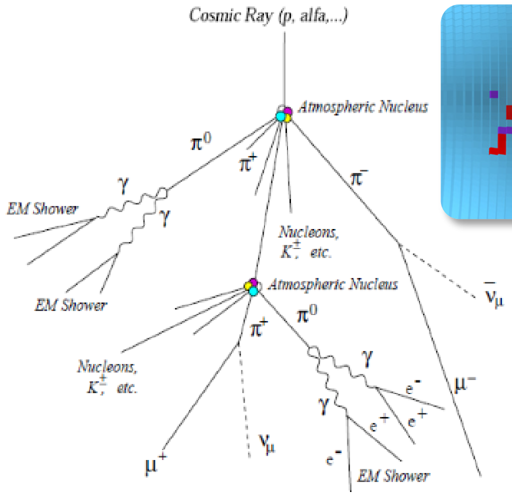
- **Direct reconstruction in EMC is very challenging**
  - EMC's size & material prevent full deposition of hadronic showers
  - Unknown momentum
  - Limited position resolution
  - Non-perfect particle identification
  - Bias in Monte-Carlo simulation

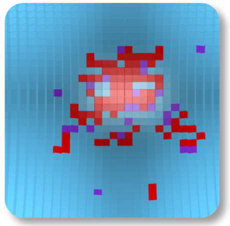
AI can be used to recognize the sparse pattern of hadronic shower in EMC.





EM shower (↑) vs. hadronic shower (↓)

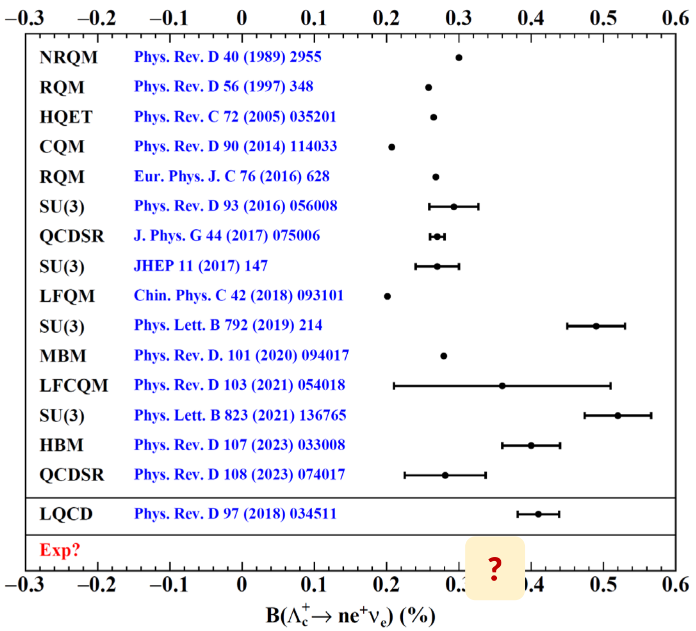




Study of $\Lambda_c^+ \to n e^+ \nu_e$ (I)

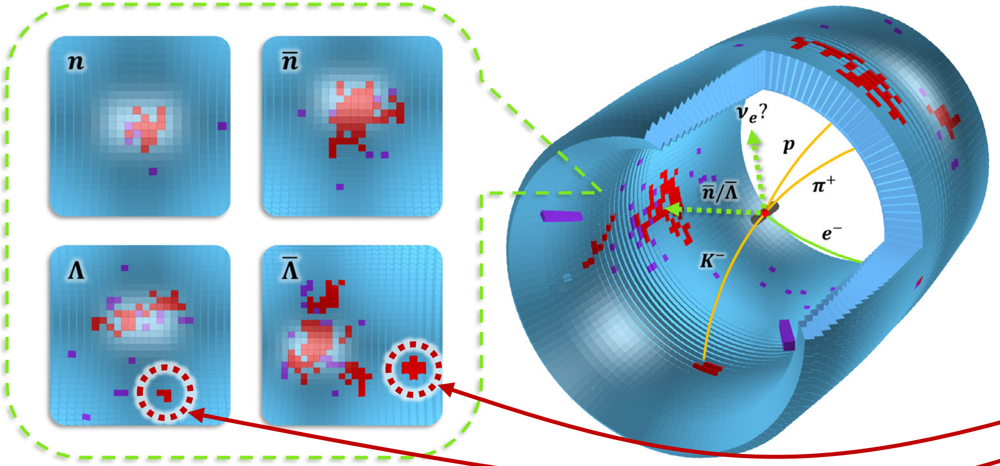
Physics motivation

- The sub-dominant Λ_c^+ semi-leptonic decay has not yet been observed
- Numerous theoretical predictions remain to be experimentally tested



Experimental challenge

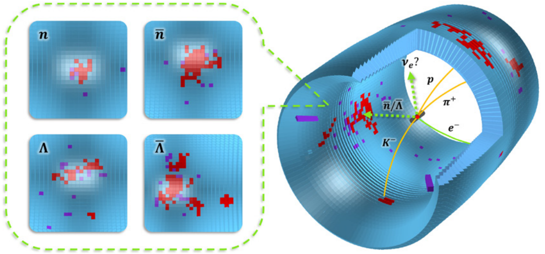
- Neutron & neutrino can't be both reconstructed with recoiling method
- Need to suppress major background $\Lambda_c^+ \to \Lambda(n\pi^0)e^+\nu_e$ efficiently
- Conventional methods fail to find signal evidence

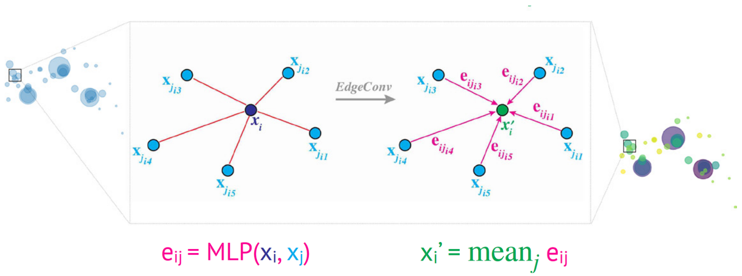


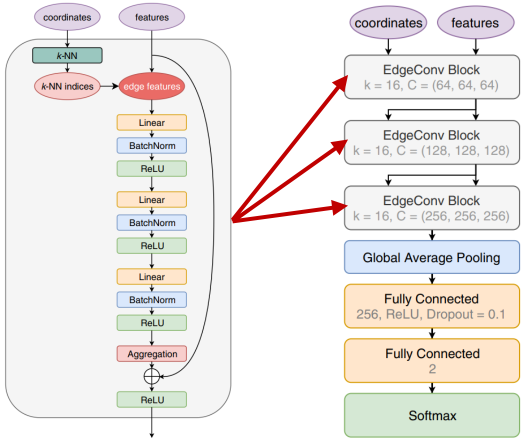
Suspected π^0-induced showers,
but can also arise from neutron, charges tracks,
beam background, detector noise, etc.

Study of $\Lambda_c^+ \to n e^+ \nu_e$ (II)

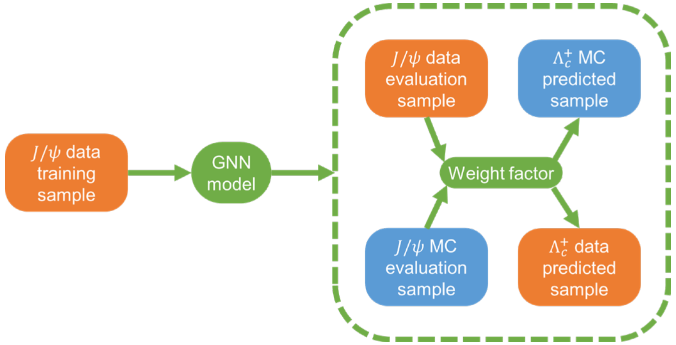
- **Neutron identification with deep learning**
  - Represent EMC showers as point cloud and process with Graph Neural Network (GNN)

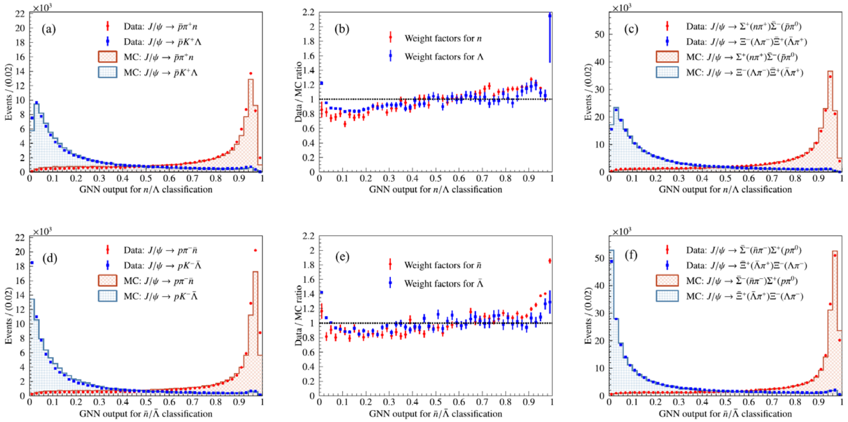






- **Extensive use of data-driven techniques**
  - Study multiple control channels including $J/\psi \to p\bar{n}\pi^-$, $p\bar{\Lambda}K^-$, $\Sigma^+\bar{\Sigma}^-$, $\Xi^-\bar{\Xi}^+$
  - For GNN model calibration, physics results validation & systematic uncertainty quantification

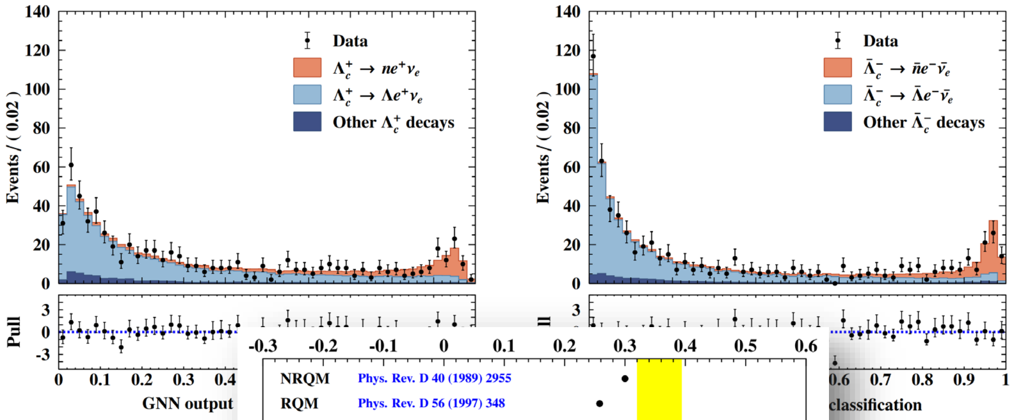


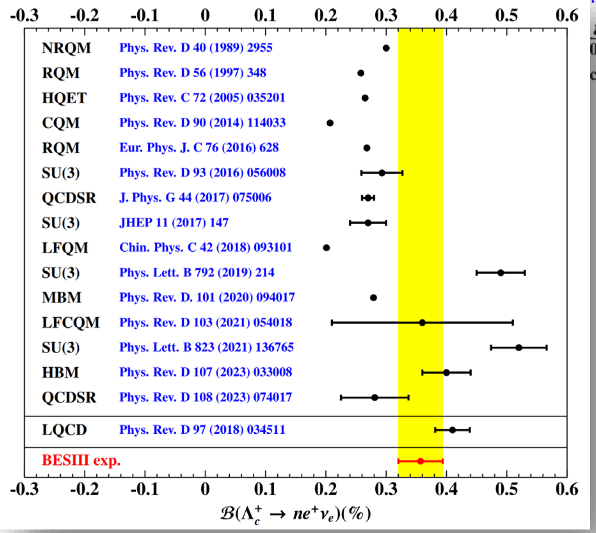


Study of $\Lambda_c^+ \to n e^+ \nu_e$ (III)

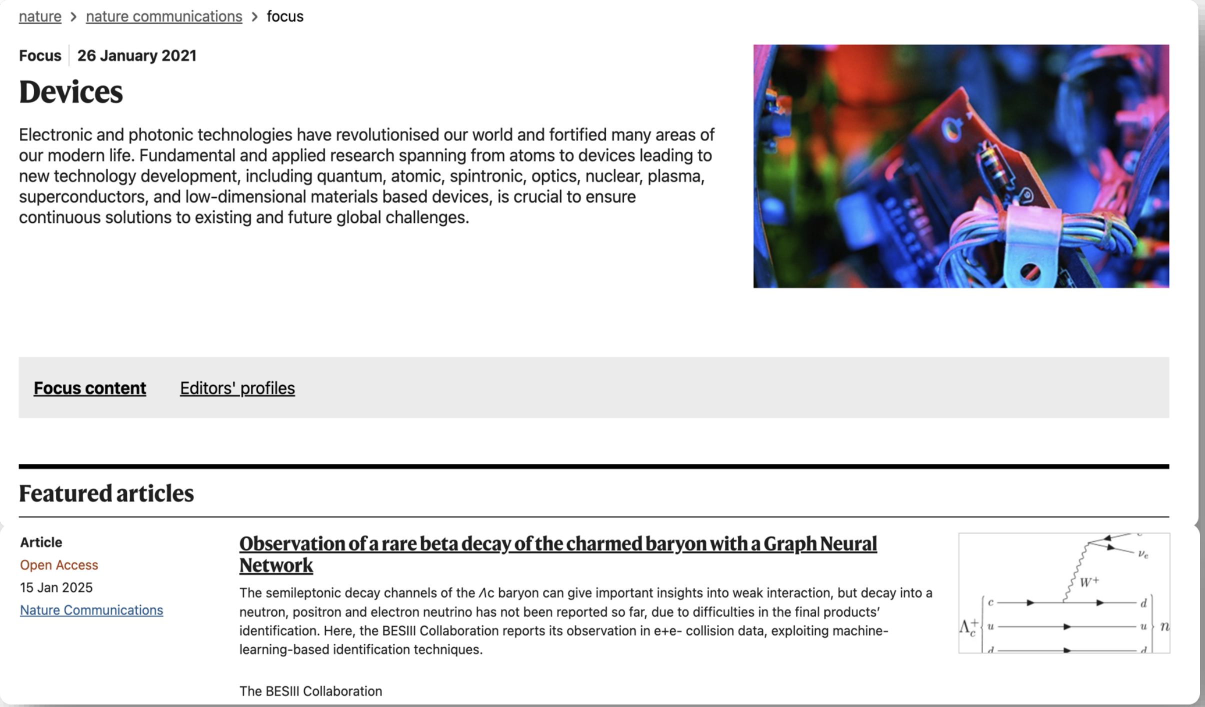
Nature Commun. **16**, 681 (2025)

- **Achieve first observation of $\Lambda_c^+ \to n e^+ \nu_e$**
  - Signal significance exceeds 10σ
  - Precision capable to examine theoretical models





Selected as Editors' Highlights in *Nature Communications*


nature > nature communications > focus

Focus | 26 January 2021

Devices

Electronic and photonic technologies have revolutionised our world and fortified many areas of our modern life. Fundamental and applied research spanning from atoms to devices leading to new technology development, including quantum, atomic, spintronic, optics, nuclear, plasma, superconductors, and low-dimensional materials based devices, is crucial to ensure continuous solutions to existing and future global challenges.

Focus content Editors' profiles

Featured articles

Article
Open Access
15 Jan 2025
Nature Communications

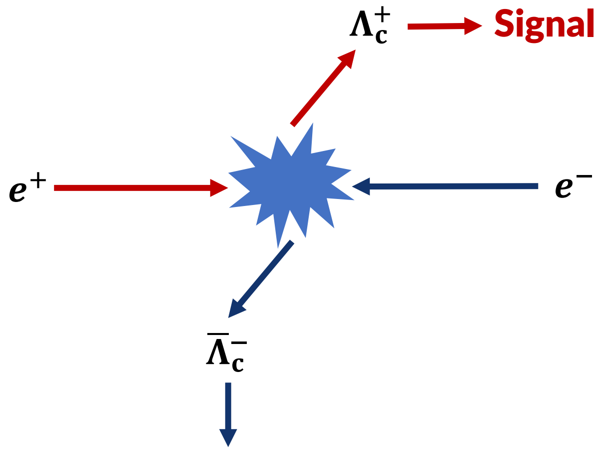
Observation of a rare beta decay of the charmed baryon with a Graph Neural Network

The semileptonic decay channels of the Λc baryon can give important insights into weak interaction, but decay into a neutron, positron and electron neutrino has not been reported so far, due to difficulties in the final products' identification. Here, the BESIII Collaboration reports its observation in e+e- collision data, exploiting machine-learning-based identification techniques.

The BESIII Collaboration

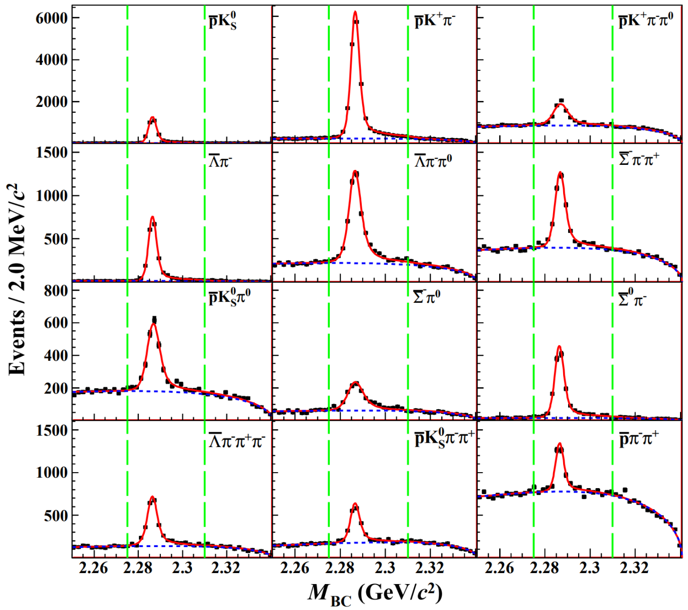
Charmed hadron tagging

- **Unique near-threshold pair-production at BESIII facilitates two tagging strategies**
  - Single-tag (ST): not constrain $\bar{h}$ decay in $e^+e^- \to h\bar{h}$
  - Double-tag (DT): constrain $\bar{h}$ decay exclusively in $e^+e^- \to h\bar{h}$



- **Current DT method has efficiency bottleneck**
  - Cover $\mathcal{O}(1)$ tag channels out of $\mathcal{O}(100)$ total decay modes
  - Only 15%~30% of $h\bar{h}$ events survive tag-side selection

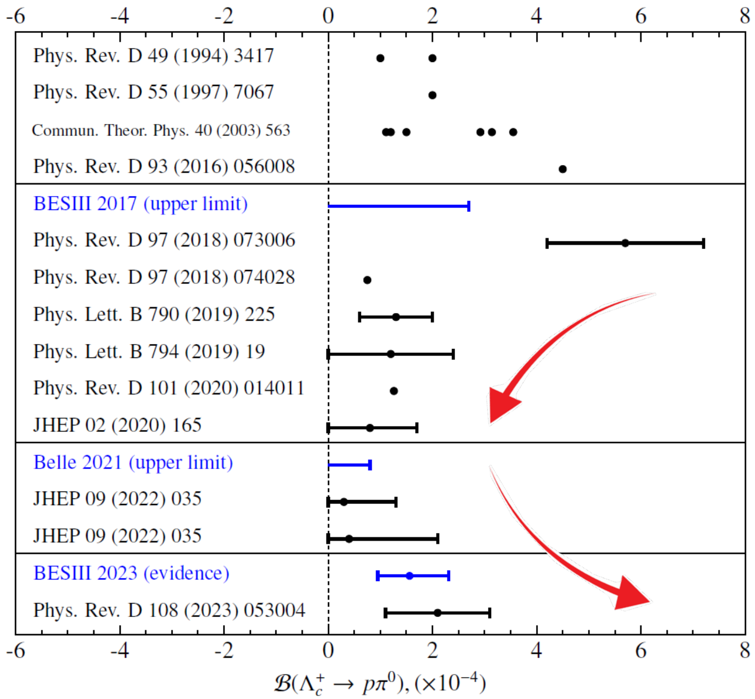
Charmed hadron	D^0	D^+	D_s^+	Λ_c^+
$\mathcal{L}_{int}$ at BESIII (fb^{-1})	20.3	20.3	7.3	4.5
# of produced $h\bar{h}$	7.2×10^7	5.6×10^7	6.5×10^6	7.6×10^5
# of tag modes	6	9	15	12
# of tagged $h\bar{h}$	2.0×10^7	1.1×10^7	9.8×10^5	1.2×10^5
Tagging efficiency	28%	19%	15%	16%



AI can be used to recognize the decay topology of $e^+e^- \to h\bar{h}$,
leading to a new tagging method that constrains $\bar{h}$ decay inclusively

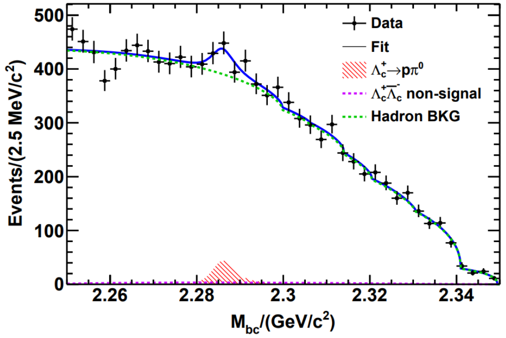
Study of $\Lambda_c^+ \to p\pi^0$ (I)

- **Physics motivation**
  - Tension in previous experimental constraints
    - Belle: $\mathcal{B} < 0.8 \times 10^{-4}$ @ 90% C. L.
    - BESIII: $\mathcal{B} = (1.56^{+0.72}_{-0.58}) \times 10^{-4}$ with 3.7σ evidence
  - Controversial experimental inputs may mislead theoretical calculations

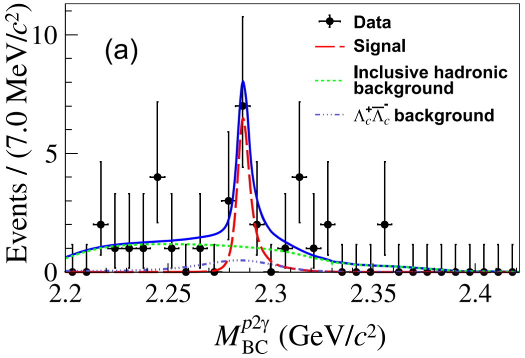


- **Experimental challenge**
  - Branching fraction around 1×10^{-4} approaches BESIII's sensitivity limit
  - Neither ST nor DT yields adequate signal significance

ST：2.6σ



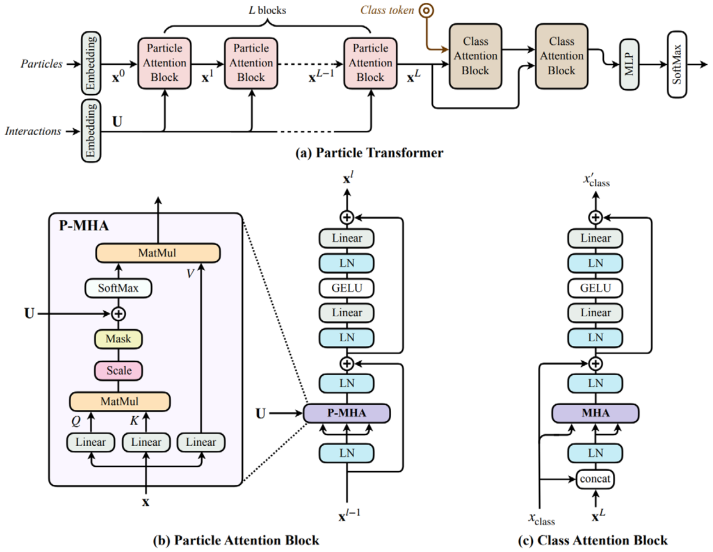
DT：3.7σ



A better efficiency-background tradeoff is desired to improve signal sensitivity

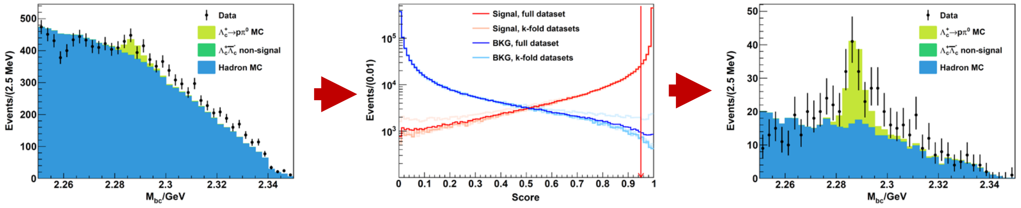
Study of $\Lambda_c^+ \to p\pi^0$ (II)

- **Inclusive Λ_c^+ tagging with deep learning**
  - Feed all charge tracks & neutral showers to a Transformer model
  - Learn to classify $e^+e^- \to \Lambda_c^+[\to p\pi^0]\overline{\Lambda}_c^-[\to \mathit{anything}]$ from backgrounds
  - Use DNN classifier to suppress background after basic event reconstruction

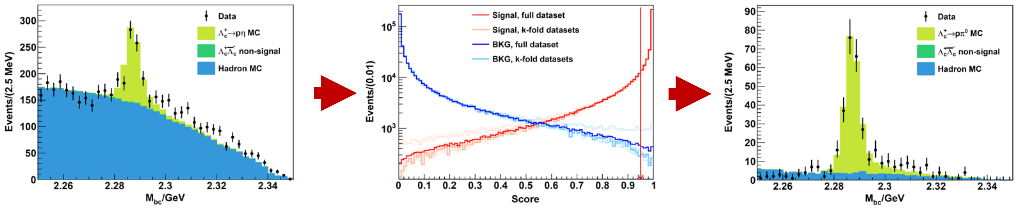


- **Extensive use of data-driven techniques**
  - Study multiple control channels including $\Lambda_c^+ \to p\eta,\ pK_S^0\pi^0,\ pK_S^0\eta$
  - For DNN model calibration, physics results validation & uncertainty quantification

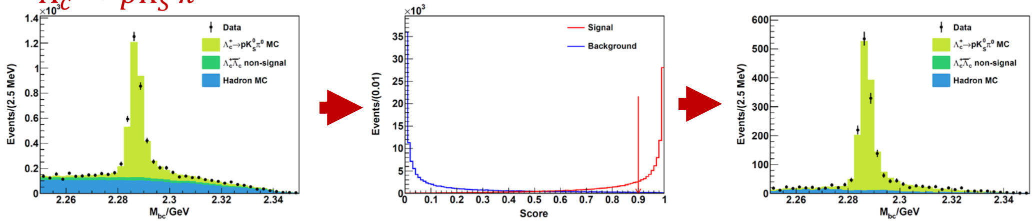
$\Lambda_c^+ \to p\pi^0$



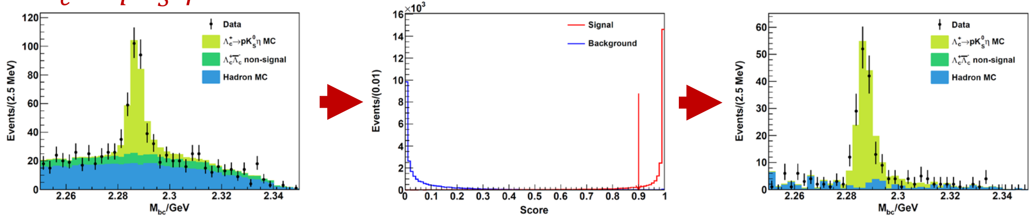
$\Lambda_c^+ \to p\eta$



$\Lambda_c^+ \to pK_S^0\pi^0$



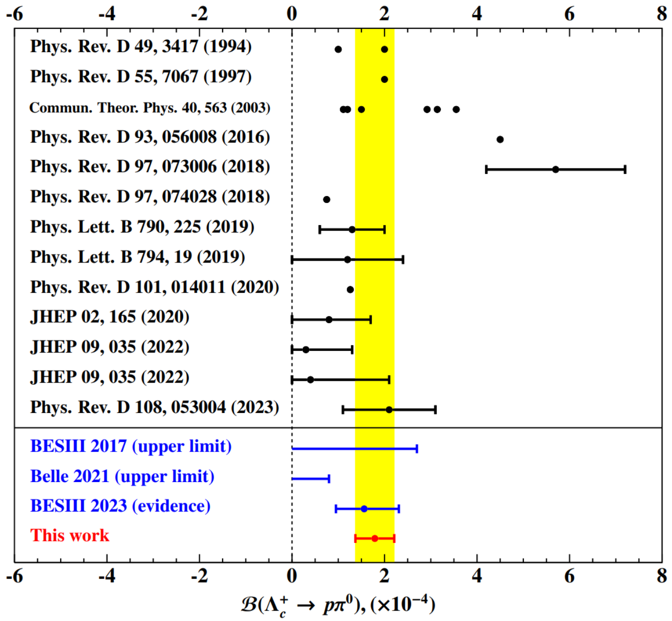
$\Lambda_c^+ \to pK_S^0\eta$



Study of $\Lambda_c^+ \to p\pi^0$ (III)

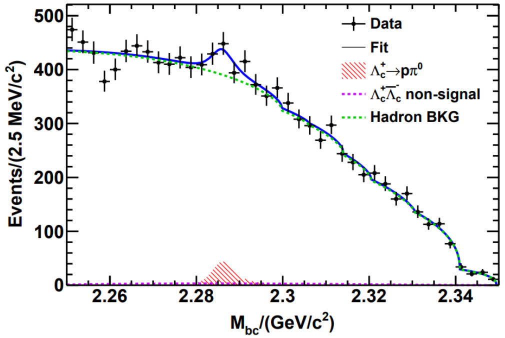
Phys. Rev. D **111**, L051101 (2025)

- **Achieve first observation of $\Lambda_c^+ \to p\pi^0$**
  - Significance reaches 5.4σ
  - Result is consistent with BESIII's evidence but exceeds Belle's upper limit

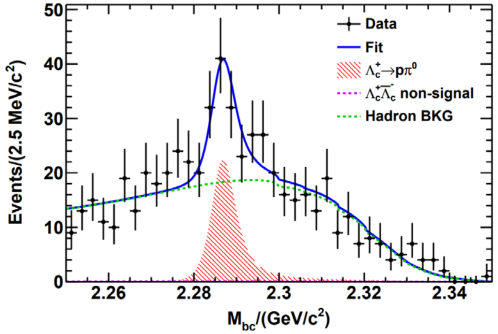


- **Method being widely applicated at BESIII**
  - Boost multiple Λ_c^+ studies including $\Lambda_c^+ \to p\eta', p\pi^+\pi^-\pi^0$, etc.

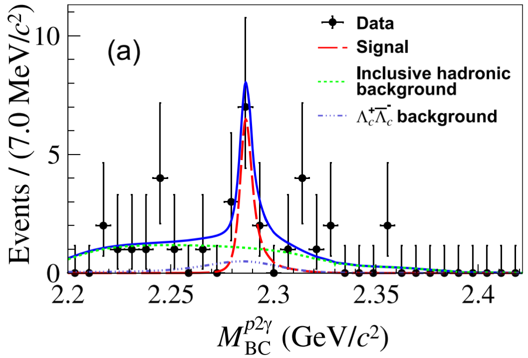
ST: 2.6σ



DNN tagging: 5.4σ



DT: 3.7σ

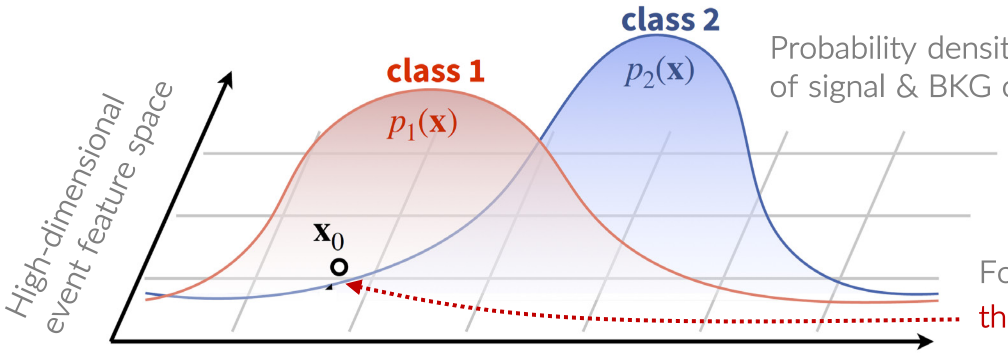


AI method improve signal sensitivity by ~1.7x compared with DT

General signal identification

- **DNN classifier can provide a unified solution for signal–background discrimination**
  - And has potential to surpass cut-based selection & BDT

- **A statistical interpretation**
  - Signal & background events form two PDFs in a high-dimensional feature space
  - The upper limit of signal/BKG identification is the ratio of these PDFs (Neyman–Pearson Lemma)
  - Such optimal classifier yields minimum cross-entropy
  - DNN can approximate this optimal by minimizing cross-entropy loss on data samples in training



Probability density functions (PDF) of signal & BKG classes

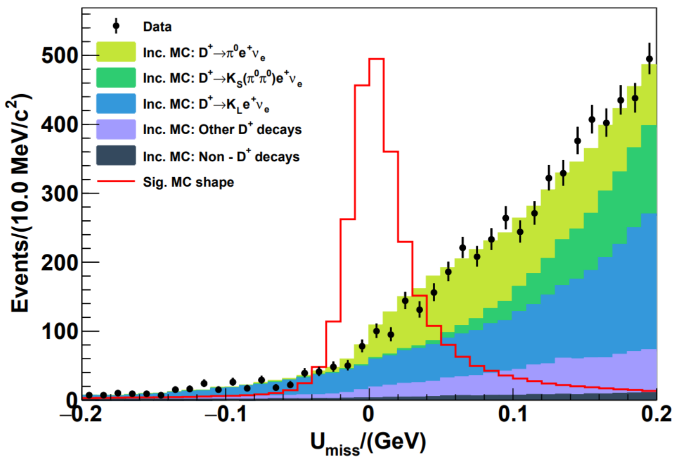
For arbitrary event X_0, the best estimation is $\frac{Prob(sig)}{Prob(BKG)} = \frac{p_1(X_0)}{p_2(X_0)}$

Study of $D^+ \to \gamma e^+ \nu_e$ (I)

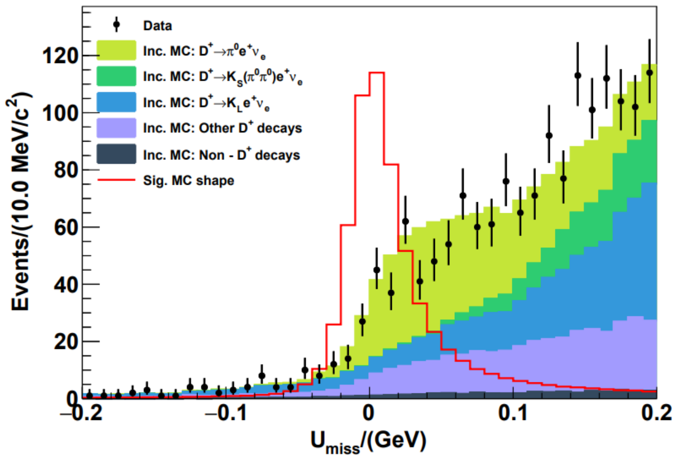
- **Physics motivation**
  - Radiative leptonic decays offer a clean probe of the SM
  - BESIII's sensitivity is approaching theoretical predictions

Model	LFQM [11]	NRQM [12]	RIQM [13]	pQCD [14]
$\mathcal{B}(D^+ \to \gamma e^+ \nu_e)$ ($\times 10^{-5}$)	0.69	0.46	3.34	8.2 ± 6.5
Model	QCDF [15]	QCDF [16]	QCDF [10]	BESIII [17]
$\mathcal{B}(D^+ \to \gamma e^+ \nu_e)$ ($\times 10^{-5}$)	2.81	1.92	$\left(1.88^{+0.36}_{-0.29},\ 2.31^{+0.65}_{-0.54}\right)$	< 3.0

- **Experimental challenge**
  - Huge contamination from D^+ semi-leptonic decays
    - BFs about $100\times$ of signal
  - Hard to identify signal radiative photon from π^0 & K_L^0-induced backgrounds



Cut-based selection



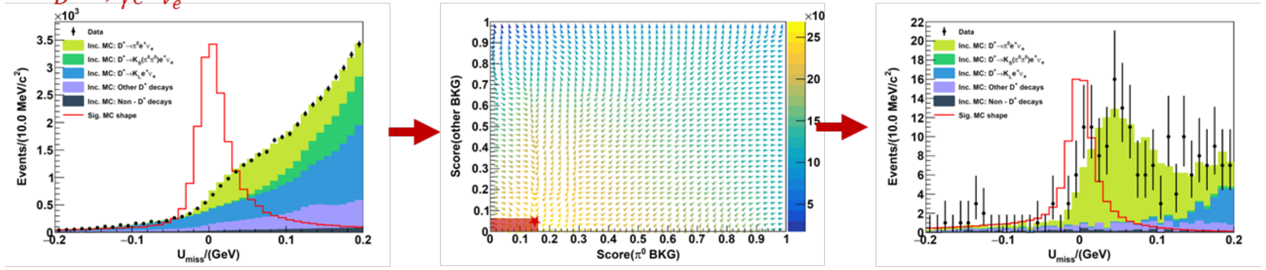
Study of $D^+ \to \gamma e^+ \nu_e$ (II)

Chin. Phys. C **49**, 083001 (2025)

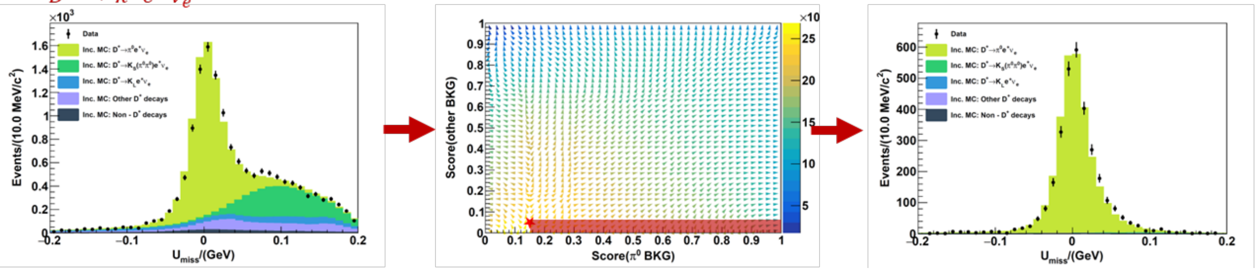
- **General signal identification with deep learning**
  - Train a 3-classifier among signal, major background and other backgrounds
  - Background channel $D^+ \to \pi^0 e^+ \nu_e$ also serves as control channel
- **Provide most stringent upper limit on decay BF**
  - Exclude most existing theoretical predictions
  - A physics goal that can not be achieved with cut-based method

Model	$\mathcal{B}$ ($\times 10^{-5}$)
Light front quark model [14]	0.69
Non-relativistic quark model [15]	0.46
Relativistic quark model [16]	3.34
Perturbative QCD [17]	8.2 ± 6.5
Lattice QCD [18]	0.09 ± 0.04
QCD factorization [19]	2.81
QCD factorization [20]	1.92
QCD factorization [10]	$\left(1.88^{+0.36}_{-0.29}, 2.31^{+0.65}_{-0.54}\right)$
BESIII 2017 [21]	<3.0
This work	< 1.2

$D^+ \to \gamma e^+ \nu_e$



$D^+ \to \pi^0 e^+ \nu_e$

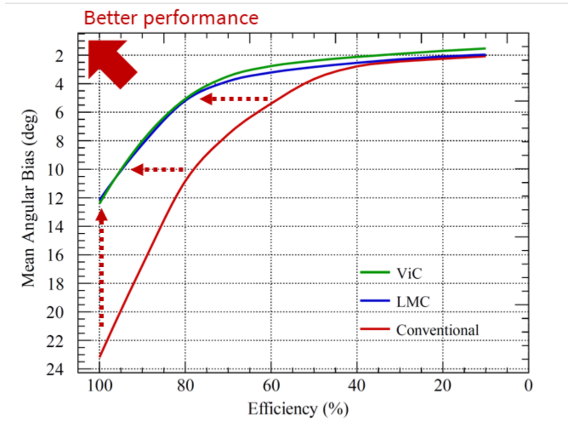


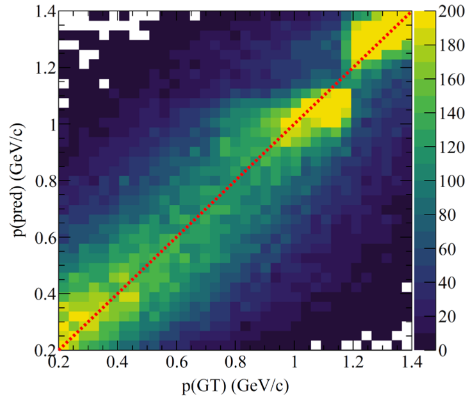
AI method achieves ~3x signal sensitivity of cut-based method

Moving forward

- **Neutral hadron reconstruction**
  - Collaborate with AI experts to develop original architectures
  - Aim for full reconstruction of anti-neutron in EMC
  - Position measurement precision improved by 90%
  - Realize momentum measurement capability for the first time
  - Well-calibrated on BESIII data using ~30 control channels

  See Yunxuan Song's talk in 2025 autumn workshop

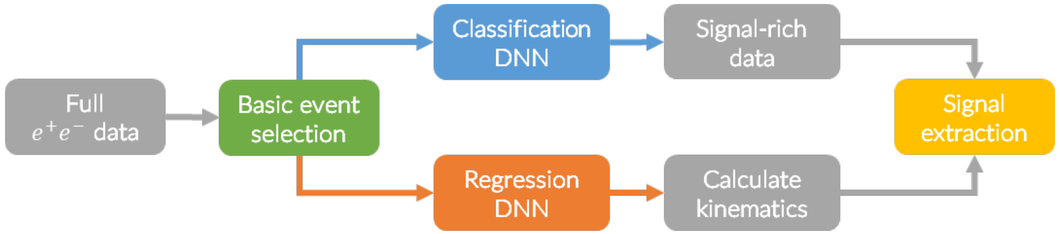




- **Charmed hadron tagging**
  - Extend AI method to study semi-leptonic decay dynamics
  - Applied to the first observation of $\Lambda_c^+ \to \Lambda(1405/1520)e^+\nu_e$

  See my talk in charm parallel session

  - Develop software packages for broader BESIII use



Summary

- **To pave the last mile of AI4HEP, it is essential to:**
  - Identify urgent experimental needs
  - Apply AI methods to real physics problems
  - Ensure reliability and robustness throughout the workflow
  - Establish a reproducible and community-accepted paradigm

- **Our team has demonstrated several successful examples:**
  - Neutral hadron reconstruction → first observation of $\Lambda_c^+ \to n e^+ \nu_e$
  - Charmed hadron tagging → first observation of $\Lambda_c^+ \to p \pi^0$
  - General signal identification → most stringent constraint on $D^+ \to \gamma e^+ \nu_e$
  - Further developments are underway

Thanks for your attention!