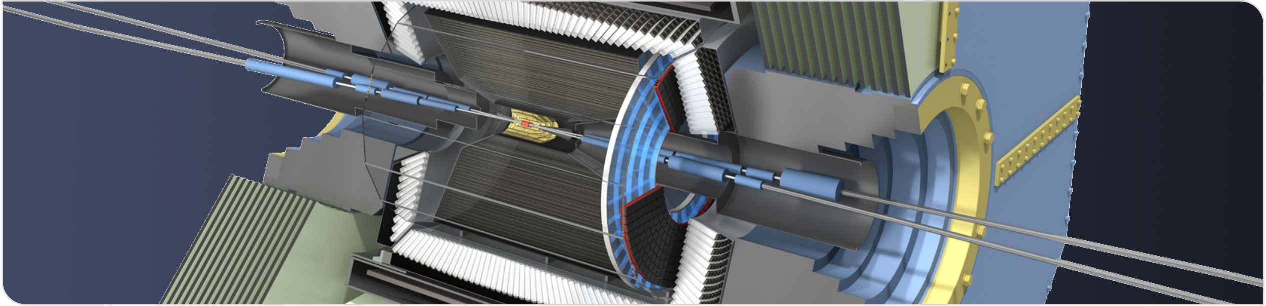
Karlsruhe Institute of Technology

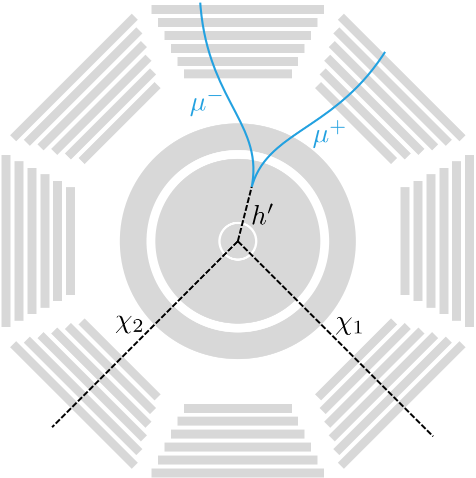
GNN-based Track and Vertex Finding

Belle II Germany Meeting 2022, Computing and Software

Lea Reuter, Philipp Dorwarth, Slavomira Stefkova, Torben Ferber | 20th September 2022



Motivation



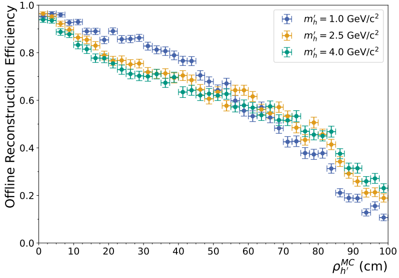
Searches for displaced vertices [a]

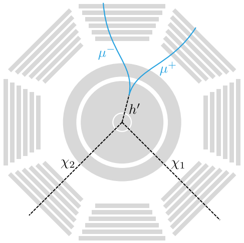
- Displaced vertices important signature in searches for new physics
- Example signal decay with dark photon A' and dark higgs h'

$$e^+e^- \to A'h',$$
$$h' \to \mu^+\mu^-,$$
$$A' \to \chi_1\chi_2,$$
$$\chi_2 \to \chi_1 e^+e^-$$

[a] Talk by Patrick Ecker : Search for Inelastic Dark Matter

Motivation





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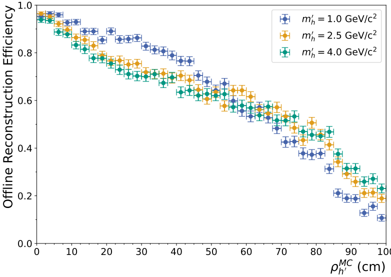

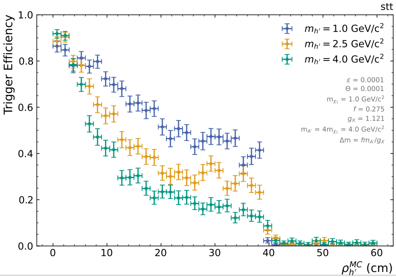

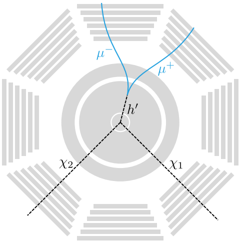

Searches for displaced vertices

- Displaced vertices important signature in searches for new physics
- Example signal decay with dark photon A' and dark higgs h'

$$
\begin{aligned}
e^+e^- &\rightarrow A'h', \\
h' &\rightarrow \mu^+\mu^-, \\
A' &\rightarrow \chi_1\chi_2, \\
\chi_2 &\rightarrow \chi_1 e^+e^-
\end{aligned}
$$

Problem:

- L1 Trigger and basf2 offline reconstruction efficiency decreases depending on displacement
- Tracks with displacement larger than 40 cm are currently not triggered

Project Goal

- **Improve Track and Develop Vertex Finding using Graph Neural Networks (GNNs):**
  - Find events with displaced vertices
  - Need to improve basf2 and online L1 Trigger reconstruction
    $\rightarrow$ starting with offline basf2, this will also improve the HLT

Project Goal

- **Improve Track and Develop Vertex Finding using Graph Neural Networks (GNNs):**
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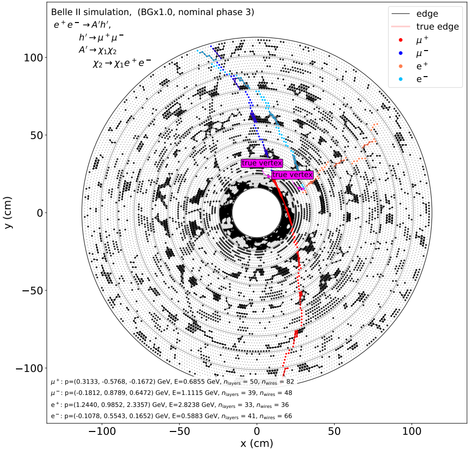
  - Need to improve basf2 and online L1 Trigger reconstruction
    $\rightarrow$ starting with offline basf2, this will also improve the HLT
- **Challenge:**
  - Tracks with low p_t (tracks curve)
  - Large occupancy due to beam-background hits (nominal phase 3)
  - Beam-background tracks (look like signal tracks)
  - Displaced vertices that are not pointing back to the interaction point

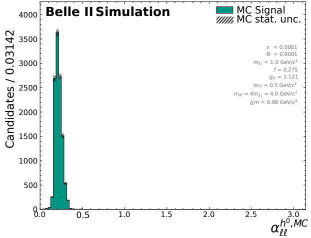


`/group/belle2/dataprod/BGOverlay/nominal_phase3/prerelease-05-00-00a/overlay/phase3/BGx1/`

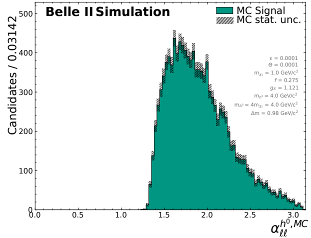
MC Simulated Samples

- Release:
  `feature/BII-9379-store-cdchit-relations-to-all-particle`
- Globaltags: `main_2022-01-27` and `patch_main_release-07`
- Starting with BGx0 and early-phase 3 BGx1
  `/group/belle2/dataprod/BGOverlay/early_phase3/release-05-01-15/overlay/phase31/BGx1/set0/`
- Signal samples:
  - Single displaced vertex samples
  - $e^+e^- \to A'h'$,
    $h' \to \mu^+\mu^-$,
    $A' \to \chi_1\chi_2$,
    $\chi_2 \to \chi_1 e^+e^-$ (outside of CDC)
  - on-shell (two-body)
  - $m(h)$ (0.5-4.0 GeV) in 0.1 GeV steps
- Background samples:
  - $e^+e^- \to e^+e^-$
  - $e^+e^- \to \mu^+\mu^-$

$m(h) = 0.5$ GeV

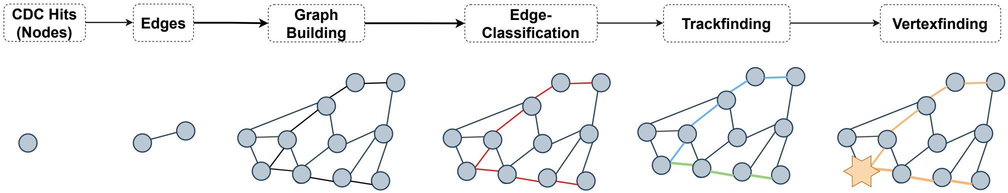


$m(h) = 4.0$ GeV



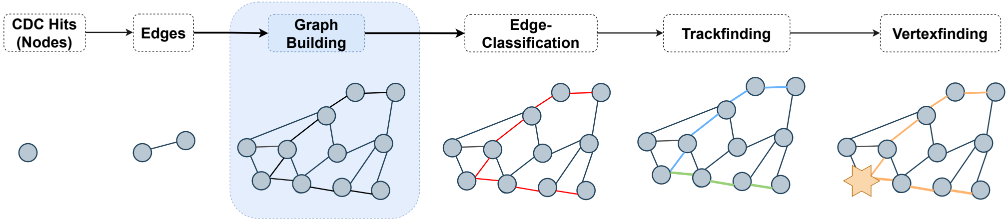
Approach with Graph Neural Networks

Variable number of CDC hits $\rightarrow$ utilize Graphs and Graph Neural Networks

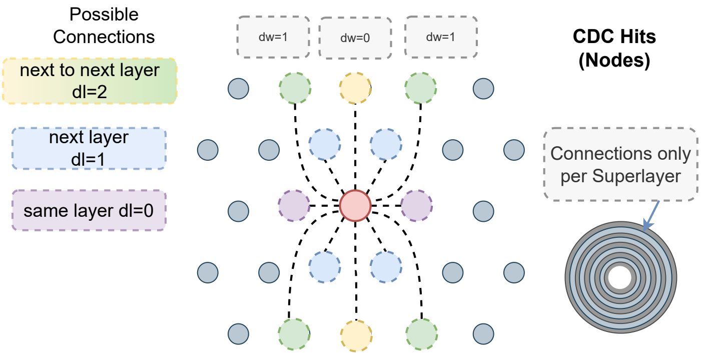


Approach with Graph Neural Networks: Graph Building

Variable number of CDC hits → utilize Graphs and Graph Neural Networks



Current Graph-Segment Building



Current Graph-Segment Building

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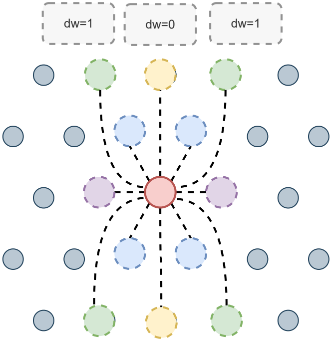
Possible Connections

next to next layer dl=2

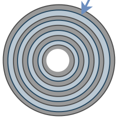
next layer dl=1

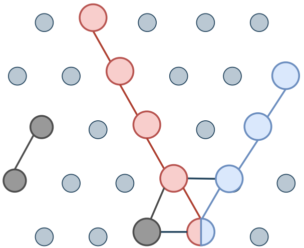
same layer dl=0



CDC Hits (Nodes)

Connections only per Superlayer





True Edge: both nodes have a CDC hit of the same MC particle

supporting multi-hits

False Edge: both nodes have a CDC hit of different MC or beam background particles

First Graph Segment Building Metrics

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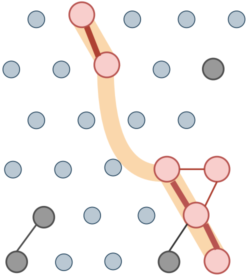
True Graph Edge:

Most efficient graph (shortest hit connections between inner and outer layers, does not have to include all hits)



next layer connections

True Graph Edge Purity:

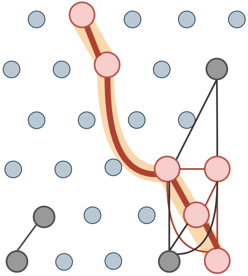
$$\frac{n_{\text{inclTrueGraphEdges}}}{n_{\text{Edges}}}$$ 3/7=43%

Included True Graph Efficiency:

$$\frac{n_{\text{inclTrueGraphEdges}}}{n_{\text{TrueGraphEdges}}}$$ 3/4=75%

Overcounting:

$$\frac{n_{\text{TrueEdges}}}{n_{\text{TrueGraphEdges}}}$$ 5/4=120%



next to next layer connections

True Graph Edge Purity:
4/14=29%

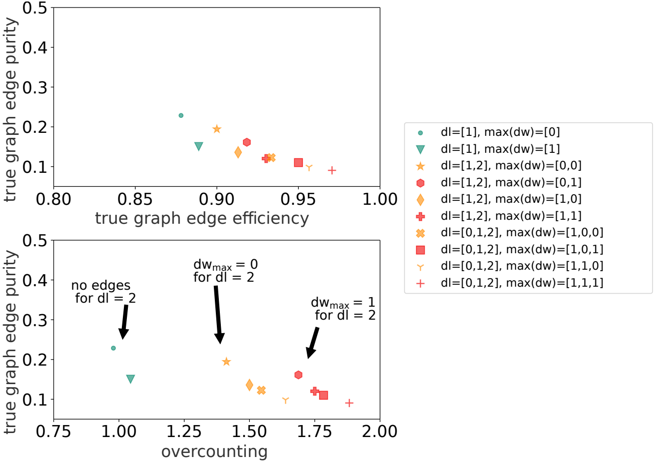
Included True Graph Efficiency:
4/4=100%

Overcounting:
8/4=175%

True Edge | **False Edge** | **Included True Graph Edge** | **True Graph Edge**

First Graph Segment Building Metrics: Evaluation

Median on 36000 samples each

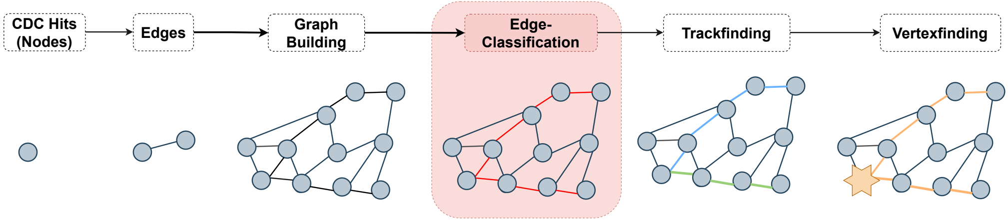


- Find trade-offs between purity, efficiency, graph size and timing
- Choice of graph building dependent on subsequent tasks
- Working together with ITIV (Department of Electrical Engineering Information Technology) at KIT for L1 Trigger graph building

Credit: Philipp Dorwarth

Approach with Graph Neural Networks: Edge Classification

Classify True and False edges of the graph

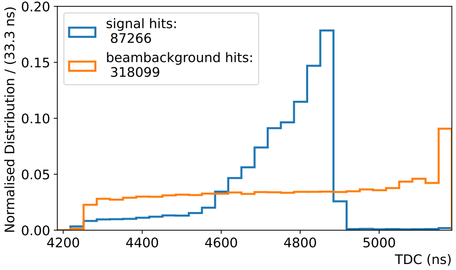


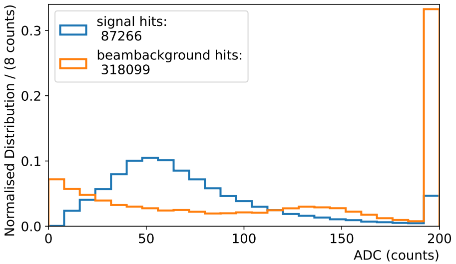
Interaction Network: Graph Neural Networks for Charged Particle Tracking on FPGAs (arxiv:2112.02048)

GNN Input Feature Studies

Testing discriminating input features:

- Nodes:
  - ρ
  - ϕ
  - digitized timing information **TDC** (online available after LS1)
  - digitized signal information **ADC** (online perhaps available for 2025)
- Edges: $\Delta\rho$, $\Delta\phi$





Edge Classification GNN Evaluation

Determine binary threshold using maximal F_1 score:

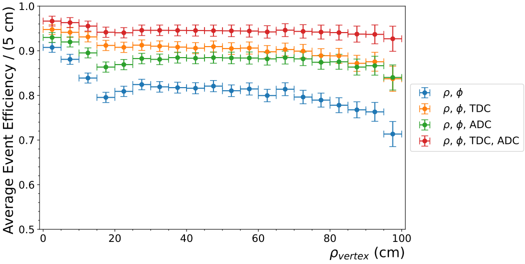
- $purity = \frac{TP}{TP+FP}$
- $efficiency = \frac{TP}{TP+FN}$
- $F_1 = 2 \cdot \frac{purity \cdot efficiency}{purity + efficiency} = \frac{TP}{TP+(FP+FN)/2}$

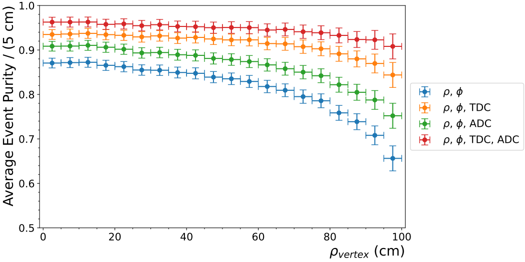
Using both TDC and ADC results in a

- Event classification efficiency of 94% and
- Event classification purity of 93%

on signal with early-phase 3 beam-background

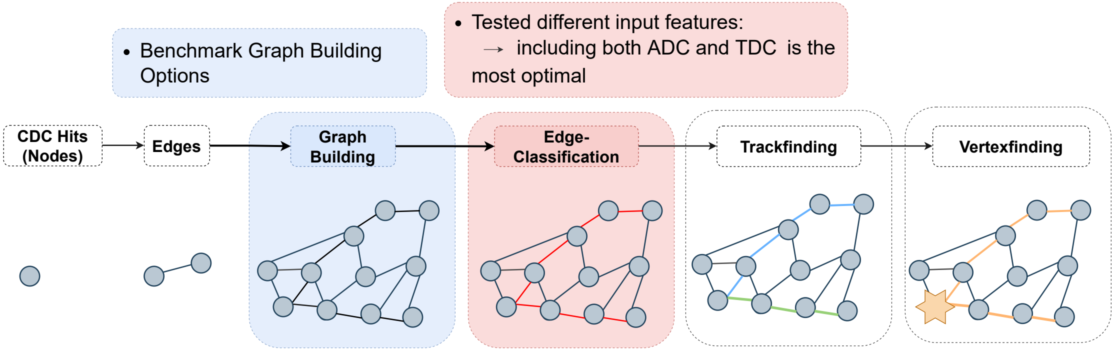
evaluated on 1000 samples per mass





Summary and Outlook

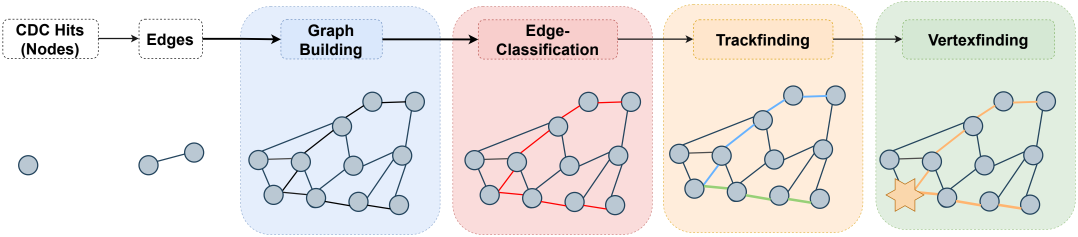
- **Displaced vertices** relevant for new physics searches
- **L1 Trigger and basf2 reconstruction** needs to be improved



Summary and Outlook

- Benchmark Graph Building Options

- Tested different input features:
  → including both ADC and TDC is the most optimal

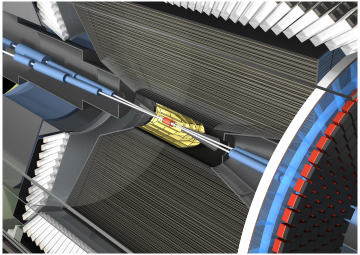


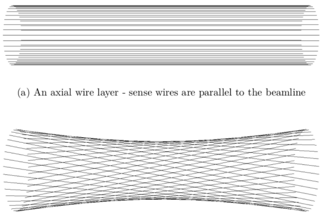
- Working together with **ITIV** (Department of Electrical Engineering and Information Technology) for **online Graph Building** and **FPGA implementation**

- **Object Condensation**[a] for Track and Vertex Finding to improve offline and online Reconstruction

[a] Talk by Isabel Haide : Improving ECL Clustering on Trigger Level with Object Condensation

Central Drift Chamber (CDC)





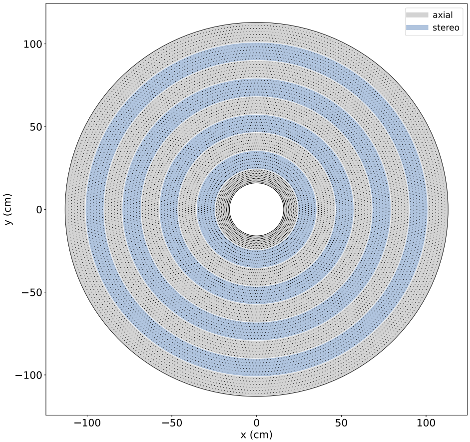
(a) An axial wire layer - sense wires are parallel to the beamline

(b) A stereo wire layer - sense wires are skewed to the beamline (exaggerated)

- Sense wires are arranged around the beamline (z-axis) to measure charged particles
- z Information gathered from stereo layers
- Events with displacement $\rho > 16.0\,\mathrm{cm}$ start within the CDC

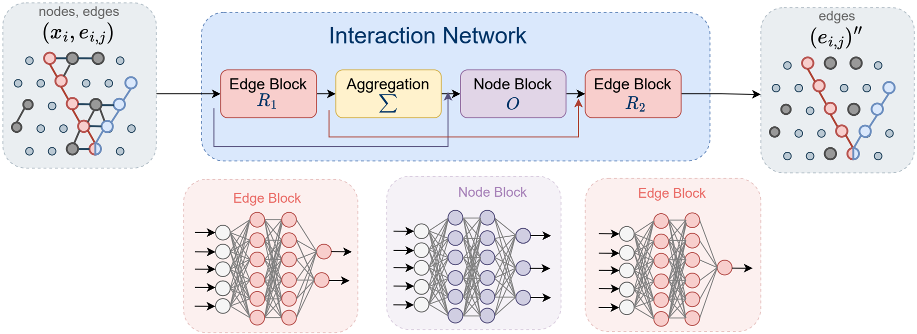
$\rightarrow$ Focus on track reconstruction using the CDC information

CDC x-y view



GNN: Interaction Network

Graph Neural Networks for Charged Particle Tracking on FPGAs
(arxiv:2112.02048)



GNN Evaluation: F_1: Input Feature Studies

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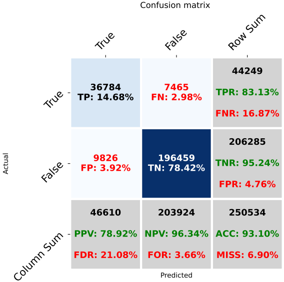
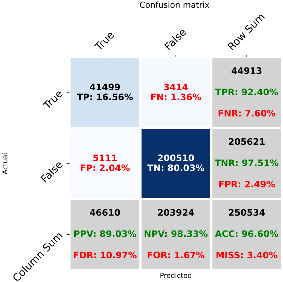
Determine binary threshold using maximal F_1 score: $F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} = \frac{TP}{TP + (FP + FN)/2}$

input features: $[\rho, \phi]$



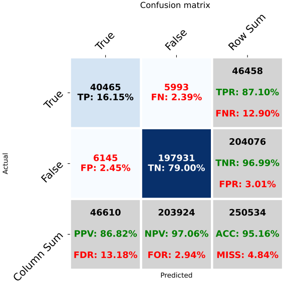
$F_1 = 0.81$

input features: $[\rho, \phi, TDC]$



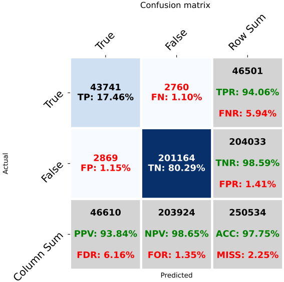
$F_1 = 0.91$

input features: $[\rho, \phi, ADC]$



$F_1 = 0.87$

input features: $[\rho, \phi, TDC, ADC]$



$F_1 = 0.94$

GNN Evaluation per Mass