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GNN-based muon energy reconstruction for INO-ICAL

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The primary goal of the India-based Neutrino Observatory (INO) is to establish an underground laboratory to study neutrinos, with a specific emphasis on atmospheric neutrinos. The focus is on obtaining precise measurements of neutrino oscillation parameters through the utilization of a 50-kiloton magnetized Iron CALorimeter (ICAL) detector. This detector has been designed to be particularly sensitive to muon neutrinos, whose energy is determined by reconstructing the energy of secondary particles resulting from charged current interactions between neutrinos and iron plates. In these interactions, muons typically carry away most of the neutrino energy. In order to accurately measure the energy of neutrinos and the oscillation parameters, a precise reconstruction of the muon energy is also essential. Currently, muon energy reconstruction within ICAL depends on a Kalman filter algorithm. This paper introduces an alternative approach based on a Graph Neural Network (GNN) for energy reconstruction. The proposed GNN method aims to evaluate its effectiveness, accuracy, and computational speed in comparison to the traditional technique. The analysis uses the data generated through Geant4 simulations of muon energy spanning from 1 GeV to 10 GeV.

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1. Introduction

The main objective of the INO, a planned underground laboratory, is to determine the atmospheric neutrino oscillation parameters and address the mass hierarchy problem. This will be achieved through the utilization of a 50-kiloton ICAL detector, composed of Resistive Plate Chambers (RPC) interspersed with magnetized plates. The facility will be located beneath a mountain in the Theni district of Tamil Nadu [1, 2]. The ICAL will be primarily sensitive to muon neutrinos, the survival probability of which is given by,

$$P_{\nu_\mu \to \nu_\mu}(t) = 1 - \sin^2(2\theta_{23}) \sin^2\left(\frac{\Delta m^2_{32} L}{4E_{\nu_\mu}}\right). \tag{1}$$

In order to measure the oscillation parameters, i.e., θ_{23} and Δm^2_{32}, a precise measurement of neutrino energy (E_{ν_μ}) is necessary . We reconstruct E_{ν_μ} from the energy of secondaries produced by the charged-current (CC) interactions of muon neutrinos with iron plates. The CC-interaction of ν_μ is given as,

$$\nu_\mu + n \to \mu^- + p. \tag{2}$$

In such an interaction of muon neutrinos, most of the energy of the neutrinos is usually carried away by the muons. Therefore, the reconstruction of muon energy is essential to derive E_{ν_μ}. In ICAL, the muon energy is reconstructed using a Kalman filter-based algorithm. In this paper, we present the first results of using a GNN-based algorithm for muon energy reconstruction in the ICAL.

2. The INO-ICAL detector

The ICAL detector is an extensive 50-kiloton huge detector comprising three modules, each measuring 16 m × 16 m × 14.5 m. 151 layers of iron plates are constructed within each detector module, each with dimensions of 2 m × 4 m × 5.6 cm, vertically spaced by a 4 cm gap. These spaces accommodate 64 units of RPCs, each with dimensions of 2 m × 2 m. The RPCs serve as the ICAL's active detection element, recording position and timing data for particles passing through them. When a muon traverses the ICAL, an RPC generates a signal in the orthogonal pickup panels situated above and below it, with a timing resolution of approximately 1 ns. Notably, the ICAL detector's magnetic field strength of 1.5 T plays a pivotal role in distinguishing between neutrino and anti-neutrino events. For additional details about the detector, see Refs [1, 2].

3. GNN for energy reconstruction

The magnetic field causes muons to have a curved trajectory as they approach the detector, where the track's curvature depends on the muon energy. Energy reconstruction currently relies on a Kalman filter algorithm, which is known for its complexity due to intricate specifications like noise covariance matrix, magnetic field details, and so on. To address computational challenges, we propose a solution to implement GNN for faster energy reconstruction, providing a streamlined alternative to the existing method.

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In our study, we represent each event as a single directed graph to perform graph classification and regression using GNN. We have chosen events where the muon has crossed at least 10 layers. The Deep Graph Library [3] is used to construct the graphs, where digitized hits serve as nodes containing spatial and temporal information and edges are created between two consecutive hits with the time difference as an edge feature.

4. Training features and datasets

The detector is simulated with Geant4 [4] to generate the training and testing datasets. We created two types of datasets for graph classification: Benchmark which lacks any vertex and angular smearing, and Smeared, which includes vertex and angular smearing. Each set contained events of mono-energetic muons with energies ranging from 1 to 10 GeV in steps of 1 GeV, forming 10 subsets for both Benchmark and Smeared datasets. During training, 80% of each dataset was used, and the remaining 20% was for testing the GNN model's performance. This allowed us to investigate how vertex and angular smearing impact energy reconstruction accuracy.

Similarly, to perform energy reconstruction using graph regression, we generated datasets by shooting mono-energetic muons. The energy range for the muons spanned from 1 to 10 GeV, with a step size of 0.1 GeV, resulting in a total of 91 subsets. We used 80% of the dataset for training the algorithm and the remaining portion was used for testing. A summary of these datasets is shown in Table 1.

Table 1: Dataset used for training and testing the GNN model. Each subset contains 1×10^4 events.

Datasets	**Subsets**	**Zenith angle (θ in degrees)**	**Momentum (GeV/c)**
A (Benchmark)	A1, A2, . . . , A10	0	1, 2, . . . , 10
B (Smeared)	B1, B2, . . . , B10	0 - 180	1, 2, . . . , 10
C (Benchmark)	C1, C2, C3, . . . , C91	0	1, 1.1, 1.2, . . . , 10
D (Smeared)	D1, D2, D3, . . . , D91	0 - 180	1, 1.1, 1.2, . . . , 10

5. Results and discussions

The classification model performed well on the Benchmark dataset (Dataset A), achieving an impressive 87% accuracy, as depicted in Figure 1 (left). However, when applied to Smeared datasets (Dataset B), the accuracy slightly decreased to around 83%, as shown in Figure 1 (right).

In order to assess the effectiveness of our regression model for the Benchmark dataset C, we plotted the true energy against the corresponding predicted values shown in Figure 2. From the plot, it is evident that the regression model successfully predicts low-energy events with a small margin of error and high-energy events are predicted with a relatively small error rate of $\approx$ 10%, demonstrating the effectiveness of our regression model.

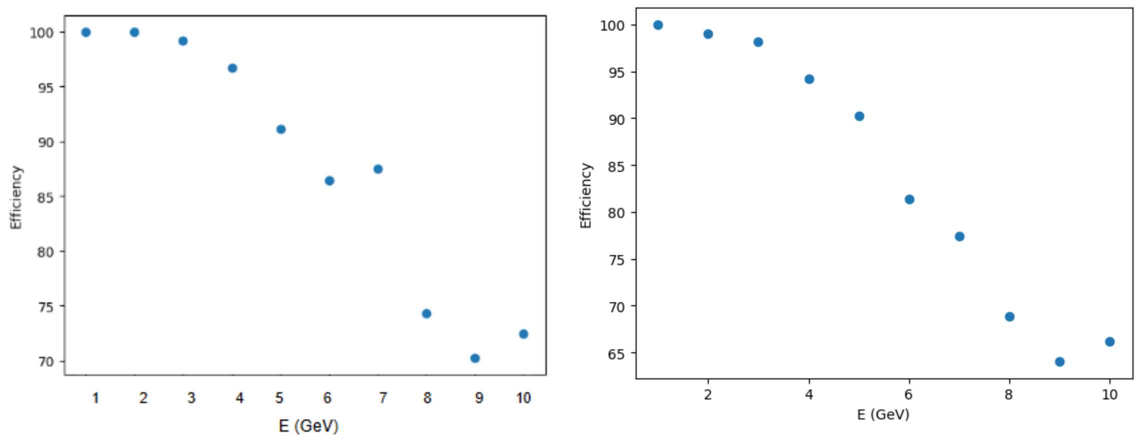

Figure 1: Comparison of classification efficiency for benchmark and smeared datasets. (Left) The reconstruction efficiency of the GNN classification model for the benchmark dataset is above 90% for energies up to 5 GeV, after which it begins to decrease. For the smeared dataset (right), the reconstruction efficiency exceeds 80% for energies up to 6 GeV, then starts to decrease.

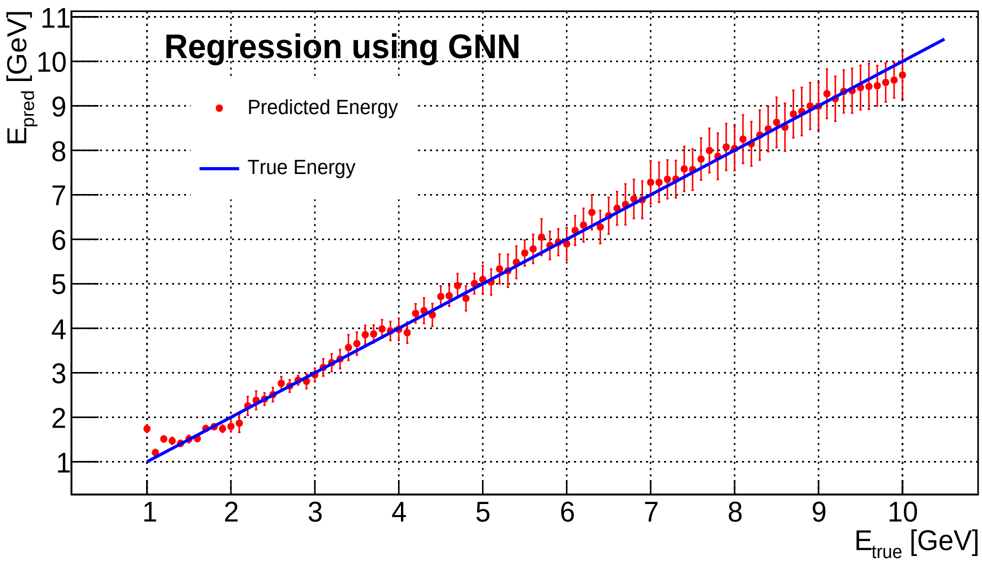

Figure 2: Energy reconstruction efficiency using the GNN regression model for the benchmark dataset. The blue line indicates the true energy values, while the red points represent the mean predicted energy corresponding to the true energy, accompanied by error bars.

6. Summary

We have successfully developed a GNN-based algorithm for energy reconstruction. The algorithm is simple and fast unlike the kalman filter-based algorithm, which requires many parameters and matrices. As a next step, we will test the regression model for the smeared dataset, and addressing the issue of decreased efficiency for high-energy events should be a priority, i.e., on how to deal with partially contained events.

References

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