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Performance of machine learning algorithm for predicting muon multiplicity in the INO-ICAL prototype

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ABSTRACT

In most of the analyses using the cosmic muon data from the INO-ICAL prototype stack, only single muon events are considered. Multi-muon events appear to be noisy events to the algorithm and thus get rejected. To address this issue, we have developed a ML algorithm technique to predict the muon multiplicity. In this work, we present the performance of this algorithm in terms of its efficiency to correctly tag multi-muon events and also to predict the multiplicity.

PROTOTYPE DETECTOR STACK

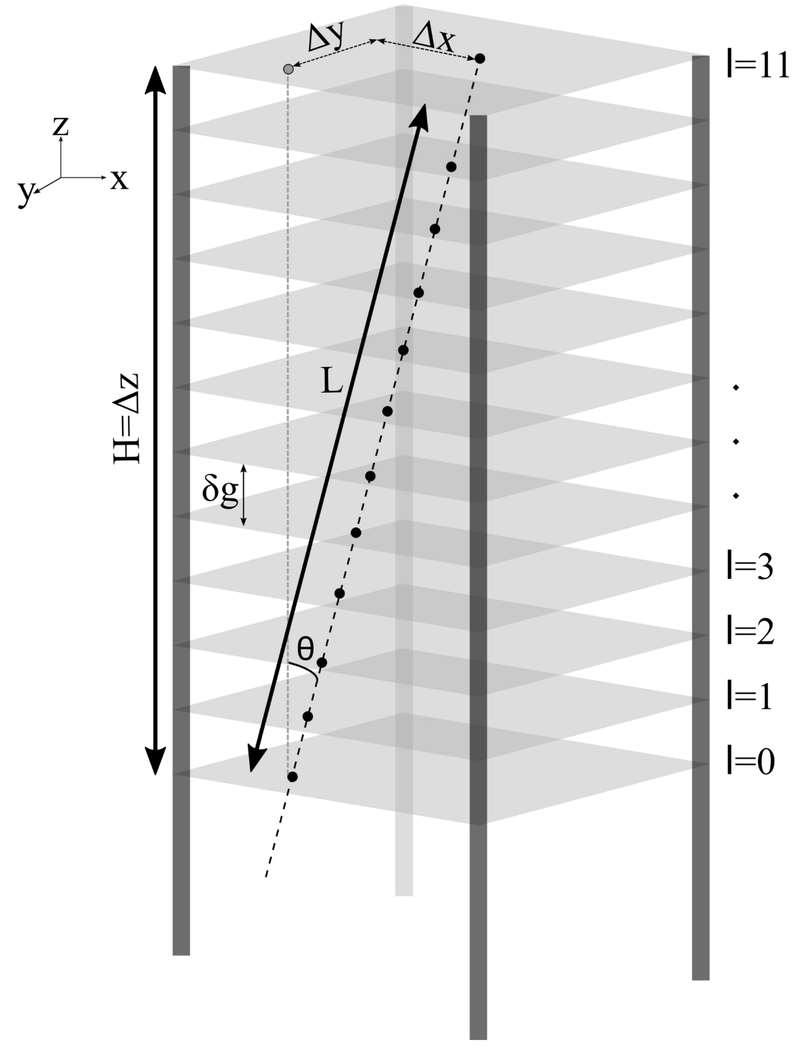
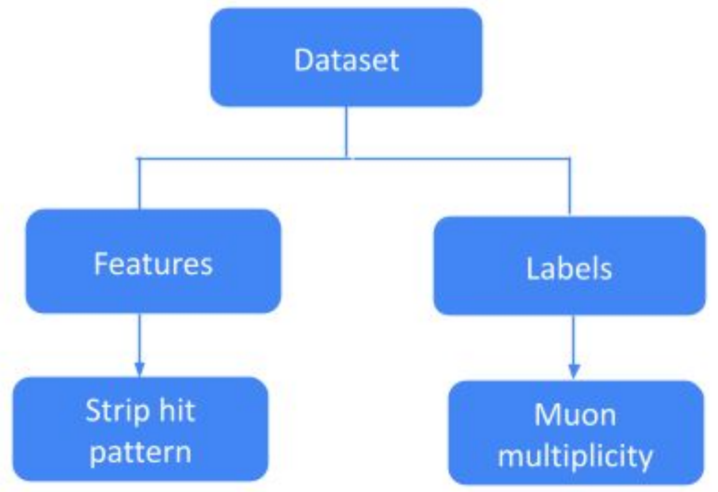


Fig.1: Schematic of the prototype stack of Resistive Plate Chambers (RPCs). It consists of 12 layers of glass RPCs of 1 m x 1 m in an area with 32 strips on each plane. The strip pitch is 3 cm. The layers are separated by a gap of approximately 16.8 cm[2]

METHOD



- Machine learning-based XGBoost Classifier model was used to predict the cosmic muon multiplicity
- The simulated dataset, generated using a simple algorithm (See adjacent section), contains strip hit patterns and corresponding multiplicities.
- Four different models were developed using the XGBoost algorithm based on four different datasets described in data generation section
- 80% of the each multiplicity data was used for training the model and the remaining 20%, used for testing the model

DATA GENERATION

- A python-based algorithm has developed to generate the dataset for training the machine learning models
- To quantify and understand the effect of detector parameters like detector efficiency(η), strip hit multiplicity (S_m = 1.5) and noise multiplicity (N_m = 3), four different datasets were generated as shown below.[1]

Dataset	No. of events for each multiplicity	Max. multiplicity	Tot. No. of events
I: Clean tracks	1000	11	11000
II: Tracks including (η=80%)	1000	7	7000
III: Tracks including η & (S_m)	1000	5	5000
IV: Tracks including η, S_m & (N_m)	1000	3	3000

Table 1. *The four datasets used for model training and testing.*

- Considered the events in which at least one track has crossed certain minimum layers (i.e trigger condition is added)
- Figure 2 describes the generation of a multiplicity 4 event with 9 minimum layers and for each of the dataset types mentioned above.

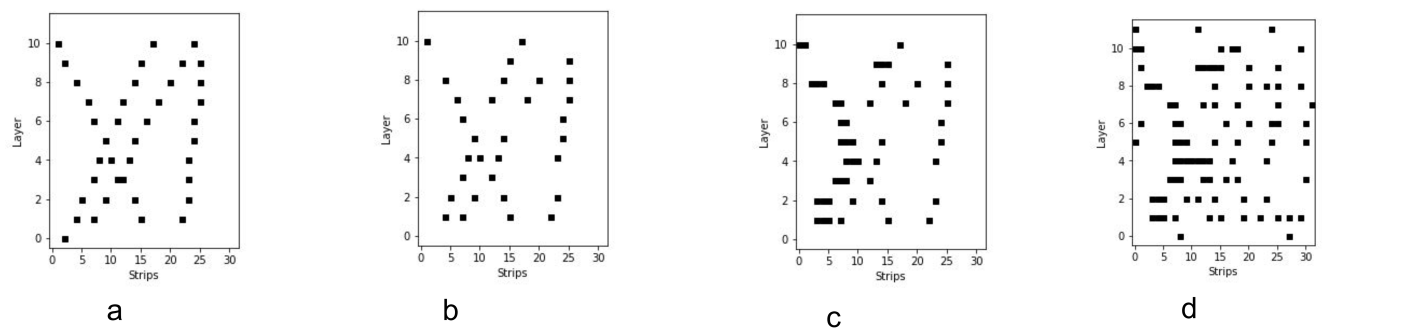


Fig.2: *Cosmic muon event from each dataset. a) Dataset I, b) Dataset II, c) Dataset III, and d) Dataset IV*

RESULTS

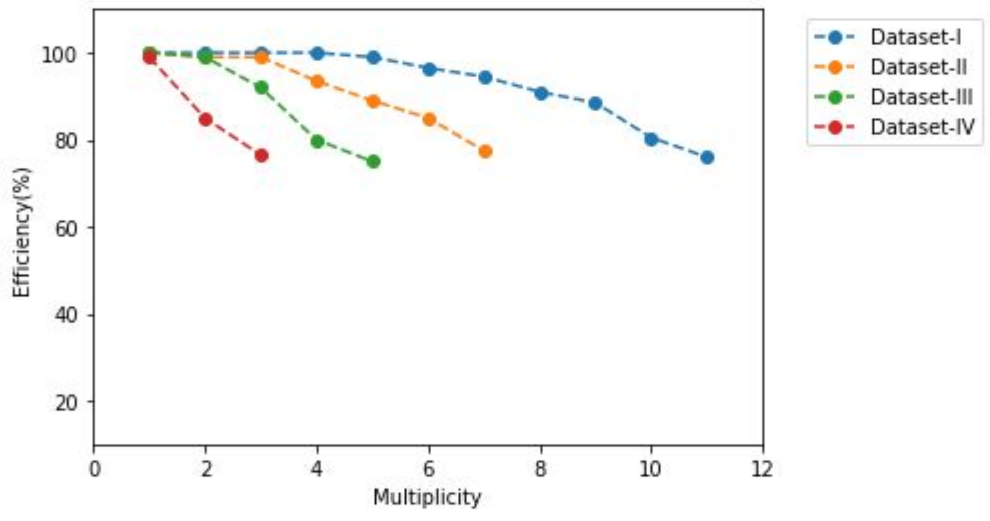


Fig.3: *Efficiency plot as a function of multiplicity for all four datasets*

- To study the performance of the models developed, the multiplicity prediction efficiency was analyzed the results are shown in figure 3.
- For clean tracks, an efficiency of 80% is observed even for a multiplicity 11 event.
- For dataset IV, the efficiency rapidly decreases to 80% even for multiplicity 3 events. Nevertheless, such events are expected to be very rare in real data.

ML Model	Time taken for training (min)	Time taken for testing (sec)
I	4.2	0.4
II	3	0.3
III	1.5	0.2
IV	0.3	0.03

Table 2. *Time taken for data generation, training and testing each model*

Computational resources

- All the datasets were trained and tested on a system with Windows 10 Pro, a 64-bit operating system, and an Intel Core i7-7500U CPU with 16 GB physical memory.
- The time taken for training and testing the model is described in table 2

CONCLUSIONS

We have presented our first results on the performance of a machine learning model to predict muon multiplicity using a machine learning model using a simulated dataset. We have used the INO-ICAL prototype detector setup as our geometry in the simulation.
We report a very high prediction efficiency of ~ 80% for muon multiplicity of 11 without noise. In the real case, due to the quality of the detectors in terms of the noise and efficiency, we expect tracks very similar to the clean tracks. However, we also notice a degradation in the prediction efficiency when extreme detector conditions are assumed (i.e detector efficiency 80%). The prediction is fast and therefore the trained model can be implemented in the DAQ code to tag multi-muons directly while writing to disc.
We intend to use this model to filter out multi-muon events from real data and carry out further analysis.

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