Applying Machine Learning to Vertex Recognition for Neutrino Interactions

Moreno Palacios Oscar Eduardo, William and Mary

FERMILAB-POSTER-23-131-ND

1. The MINERvA Experiment

MINERvA studies ν_{μ} interactions with six nuclei: oxygen, hydrogen, iron, lead, carbon , and helium.

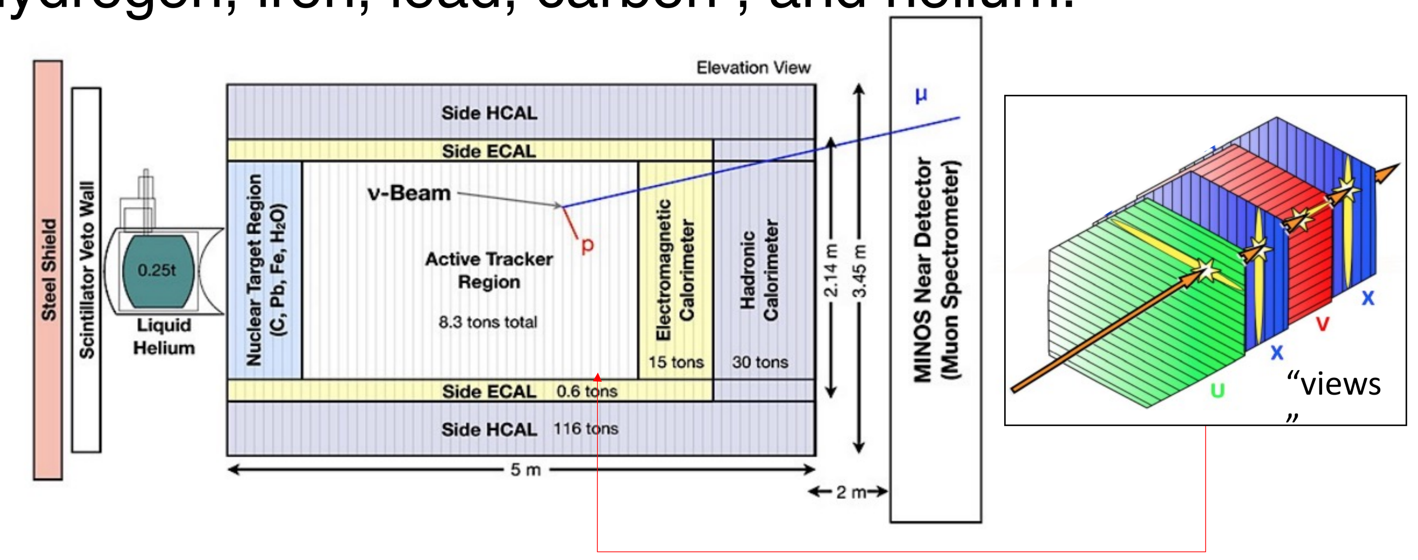


Fig 1. MINERvA detector.

- The Electromagnetic Calorimeter (ECAL) is made with lead and plastic scintillator. Pb in ECAL has 4.5 times more fiducial mass than Pb from nuclear target.

2. Motivation: Why Machine Learning?

Vertex mis-reconstructions can result from passive materials surrounding with active materials. MINERvA already improved vertexing using Machine Learning (ML)[2].

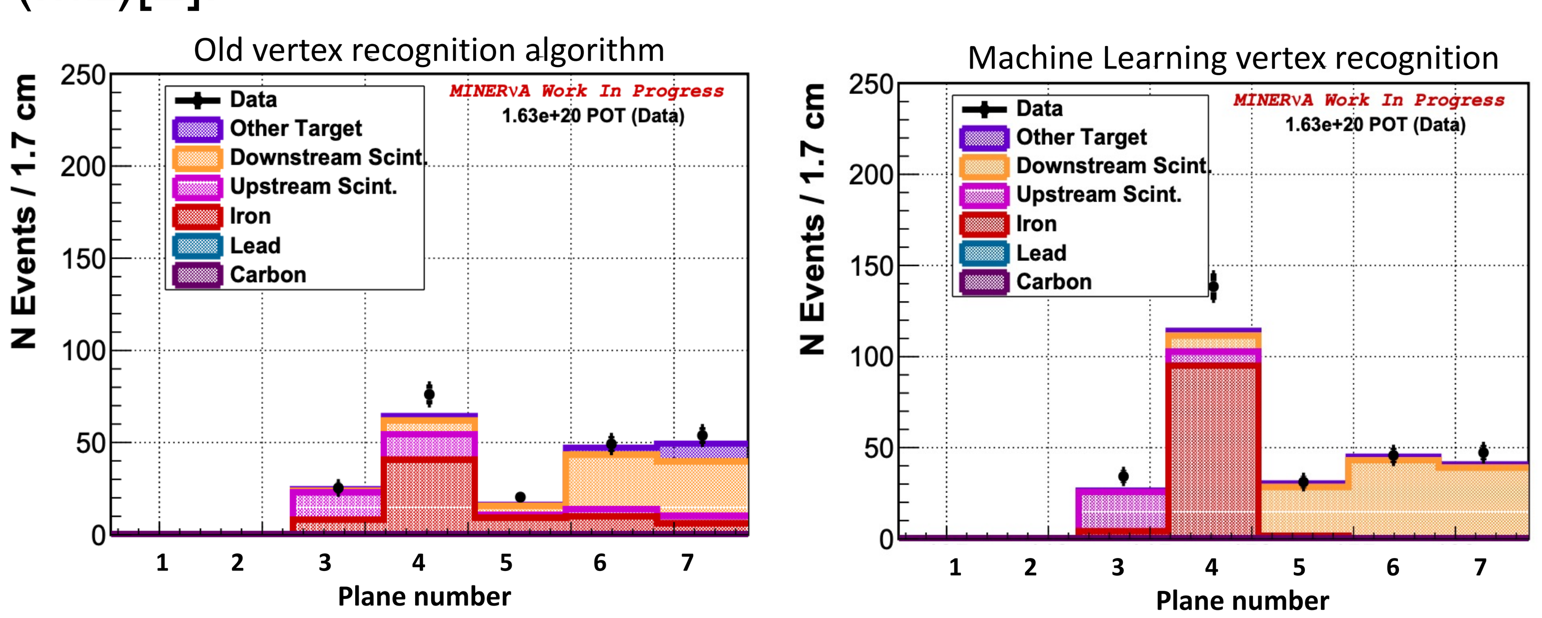


Fig 2. Comparison with ML and previous vertexing algorithm used.

Those ML models are limited to the nuclear target and tracker region. The Monte Carlo in the downstream tracker region does not match with the data. Improvements are needed here.

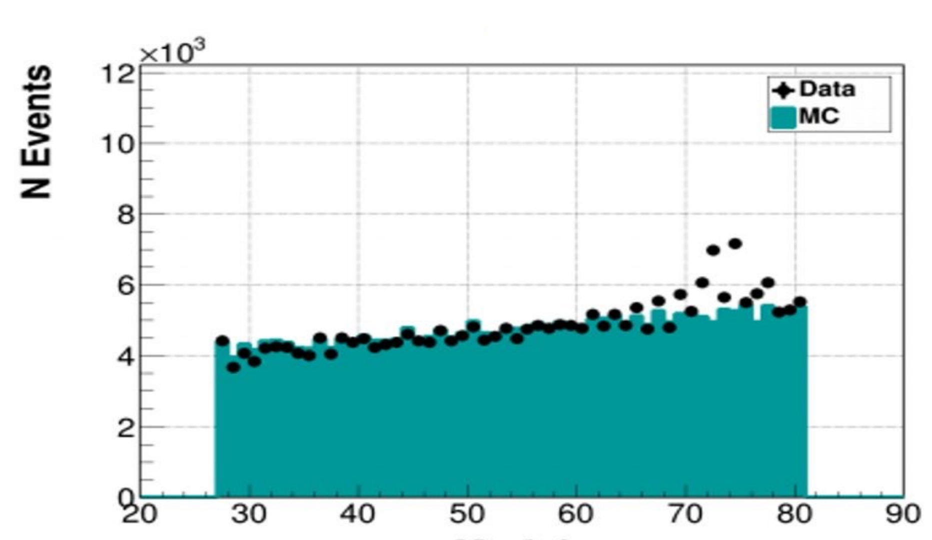
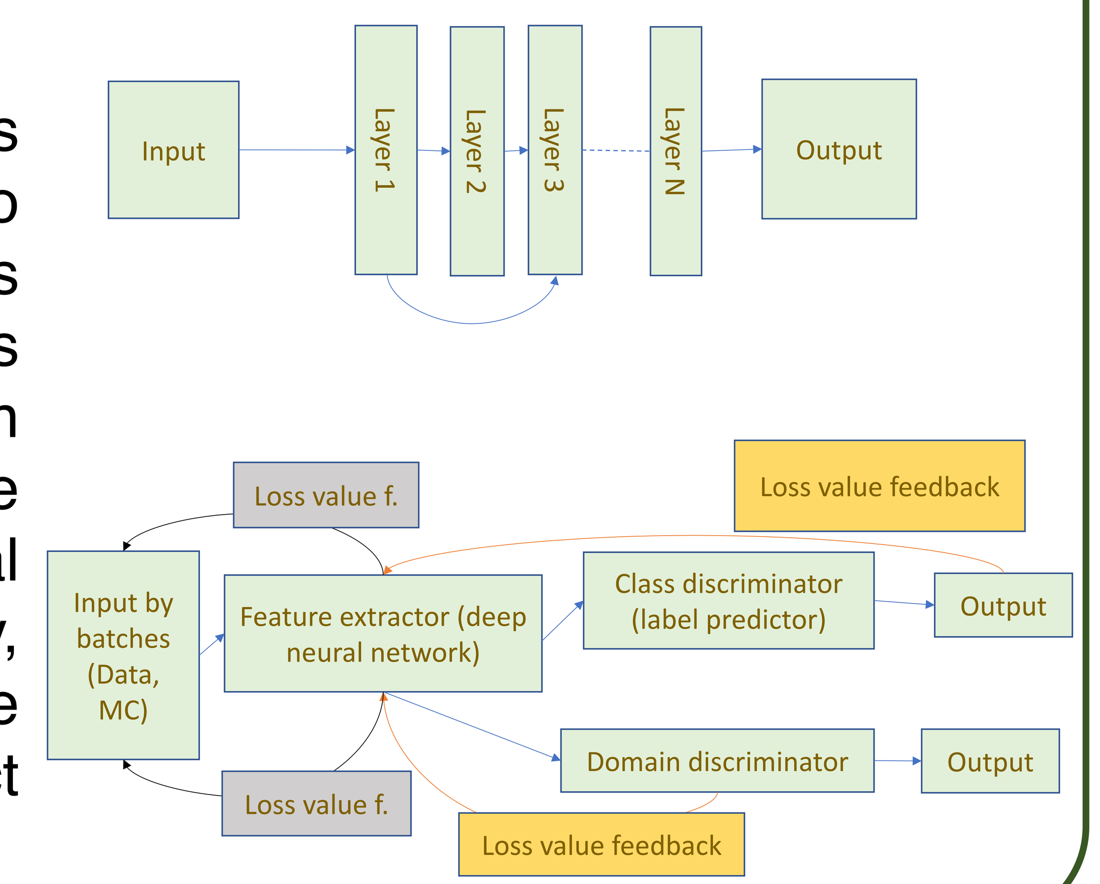


Fig 3. Event rate of Machine Learning in tracker. 1 module is equivalent to 2 planes.

- The lead located in the ECAL is a promising candidate for neutrino analysis due to its superior acceptance and nuclear mass compared to the lead in the nuclear target.

3. Neural Networks

- Two Neural Networks are used. **Deep Convolutional Neural Networks** are employed for pattern recognition, and a **Domain Adversarial Neural Networks** to penalize differences between simulated and real data.
- Training performance is evaluated using two metrics: the loss function, which yields larger values when predictions deviate significantly from actual results, and accuracy, which indicates the frequency of correct predictions.



4. Applying ML to MINERvA events

Dataset.

- Simulated data ~ 10 million images. It is separated in 3 sub-datasets: Training (80%), validation (10%), and test (10%).
- Real data ~ 2.5 million images.
- Training and validation dataset are used in the model production. The test set is used in a later stage. The simulation is labeled with the actual interaction location (plane).

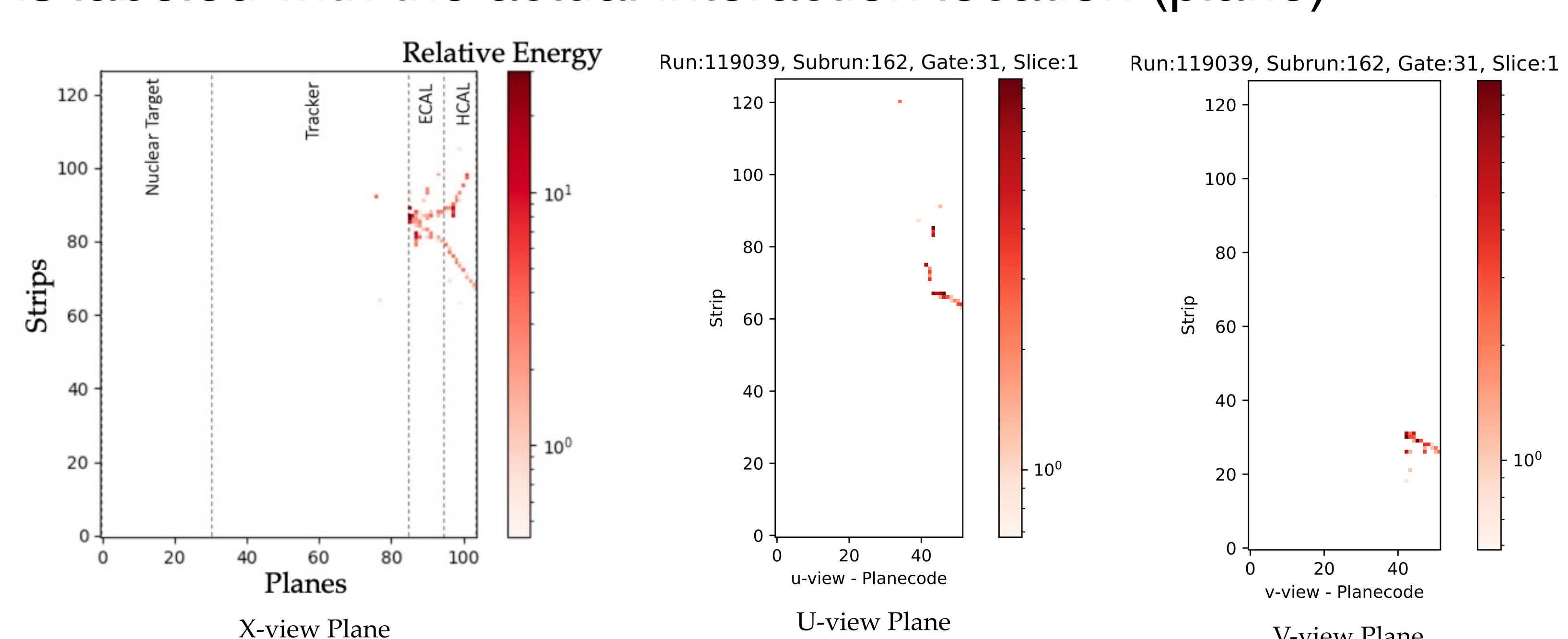


Fig 4. x,u and v views of a neutrino interaction in the ECAL.

- **Metrics for model performance.**

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN} \qquad F1 = \frac{2(recall)(precision)}{recall + precision}$$

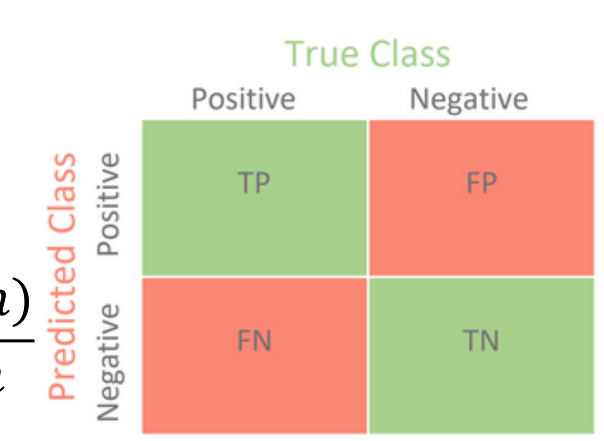


Fig. 5. Binary Confusion Matrix

Precision and recall are in a trade-off relationship and F1 score takes the harmonic mean of the two values, representing a balanced mean.

5. Training and validation

Training dataset passes through the algorithm several iterations, each time is called epoch.

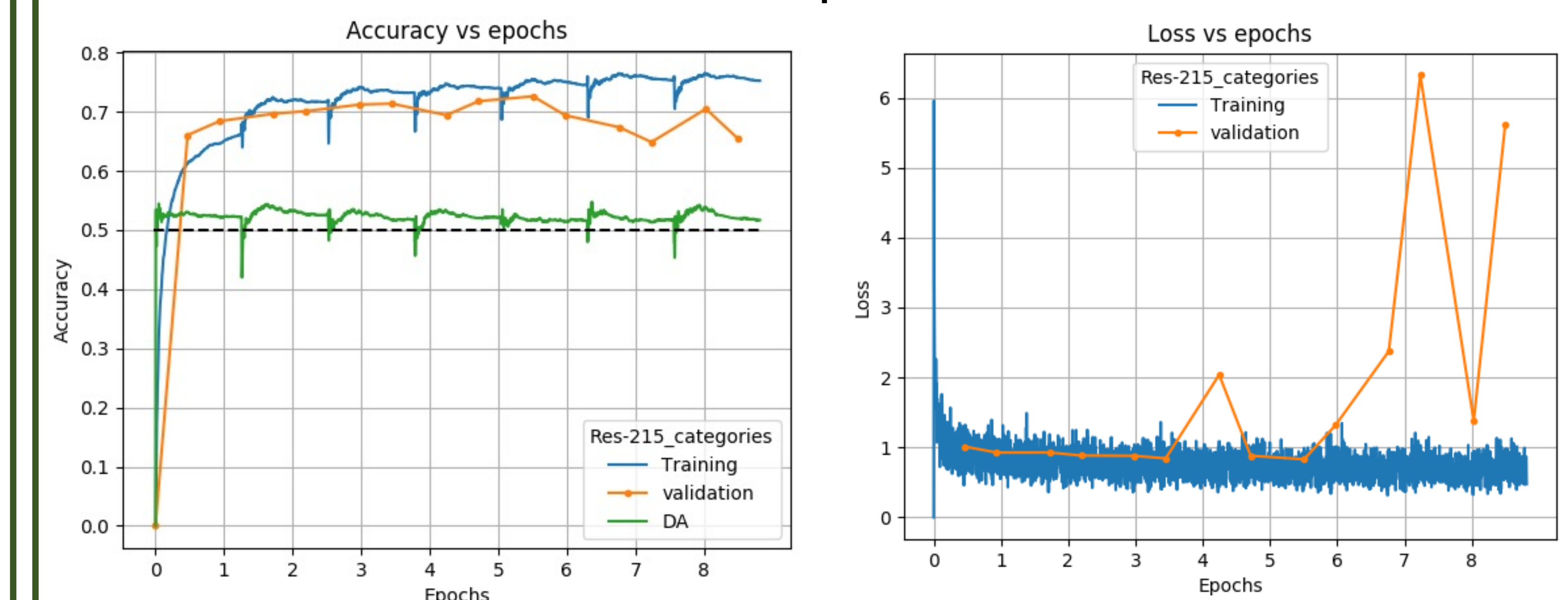


Fig 6. Validation dataset is heldback from training to assess the model. The Domain adversaial (DA) line indicates the indistinguibiblitiy beween the domains

Epoch	1.8	2.5	3.1	3.7	4.4	5.0
Accuracy	0.707	0.702	0.715	0.718	0.715	0.723
Loss	0.841	0.869	0.811	0.820	0.904	0.809

Table 1. Testing models generated in the training stage with a different dataset.

6. Model Performance

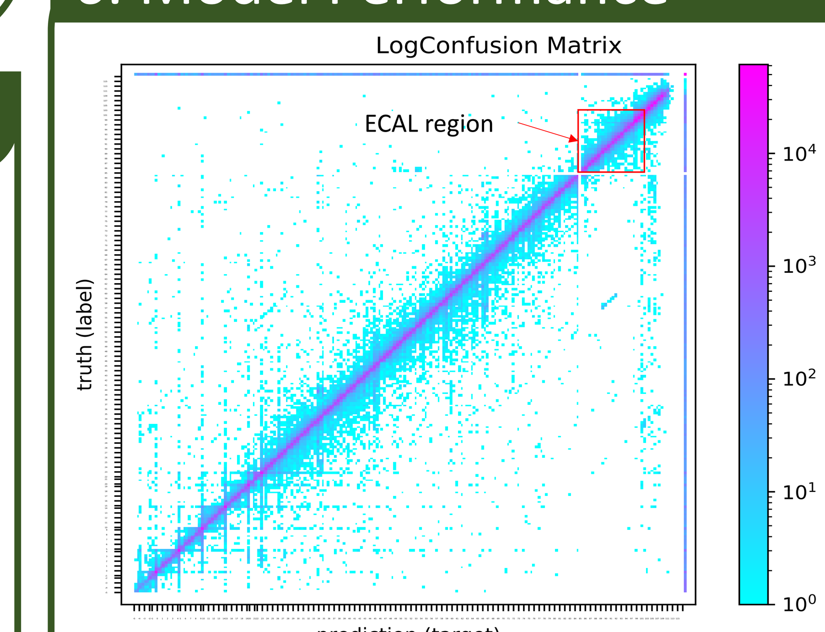


Fig. 7. Classified planes vs truth planes

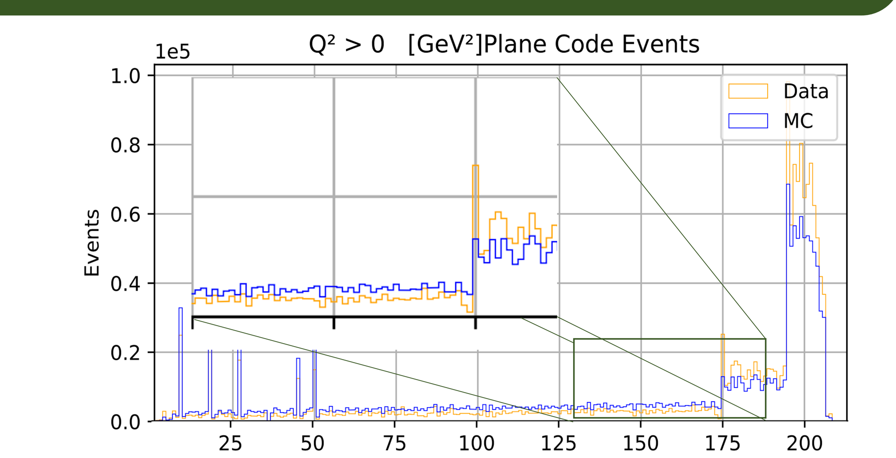


Fig. 8. MC Data comparison with new ML model.

Region	F1 mean
Target	64.4%
Tracker	67.1%
ECAL	71.3%
HCAL	72.4%

Table 2. F1-score mean by detector regions

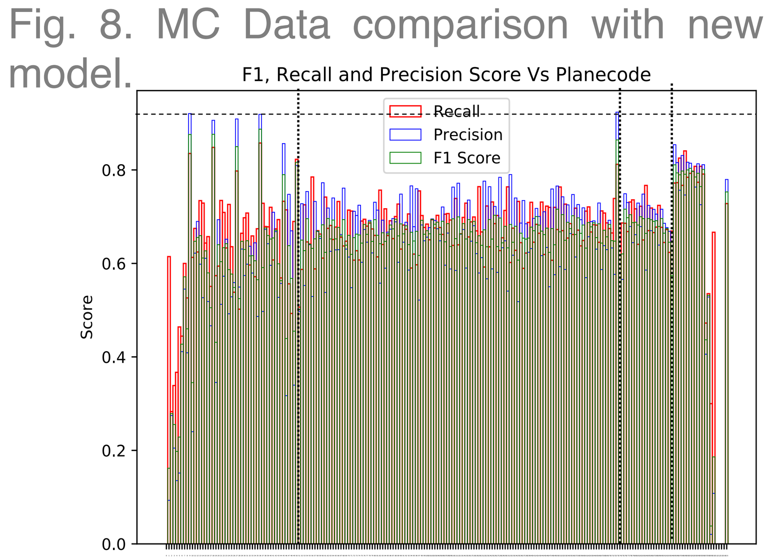


Fig. 9. F1 score for each detector plane.

7. Conclusions

- A generalized model including ECAL/HCAL activity was developed.
- This work improve vertexing downstream tracker and enable neutrino analysis in the ECAL, made of scintillator and lead.

8. References

[1] **Deep Residual Learning for Image Recognition,** arXiv:1512.03385

[2] **Vertex finding in neutrino-nucleus interaction: A Model Architecture Comparison,** arXiv:2201.02523

9. Acknowledgments

Under the supervision of Professor Jeffrey Nelson, we acknowledge the MINERvA experiment, the National Science Foundation, and the U.S. Department of Energy for providing the necessary data and support for this work.