Poster ID #500

Machine learning-based particle identification of atmospheric neutrinos in JUNO

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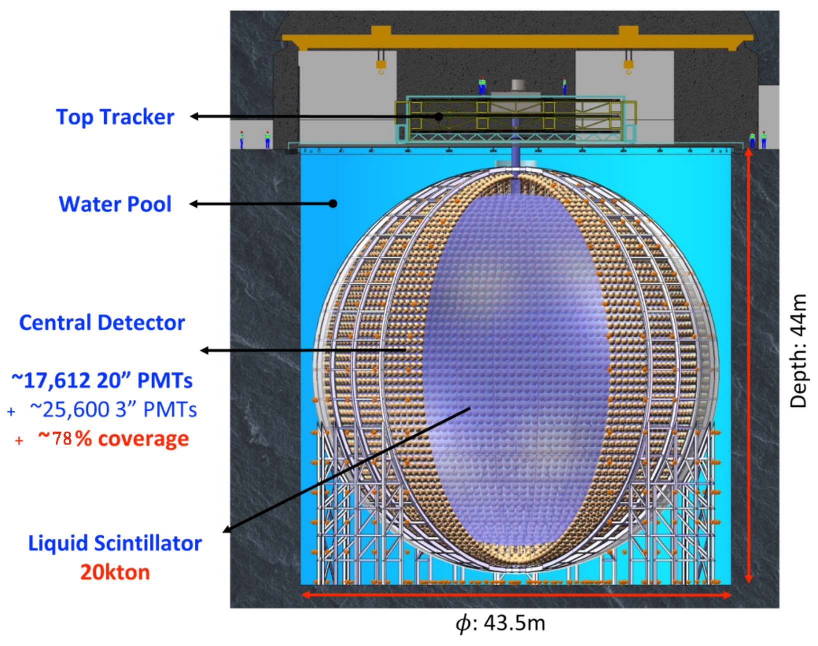
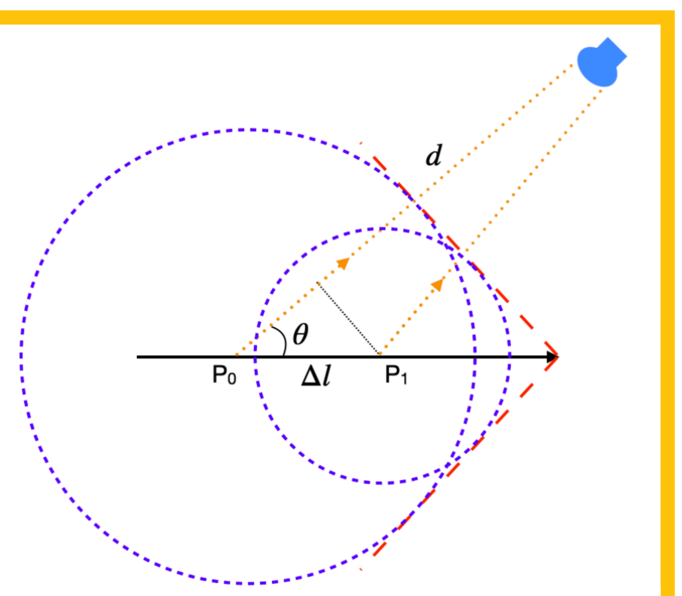
1. Overview

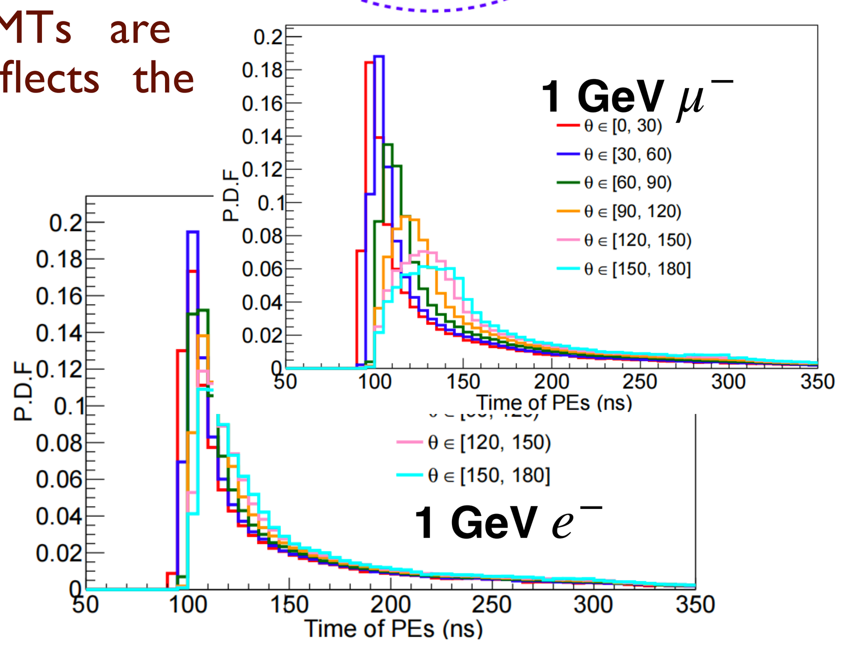
- The Jiangmen Underground Neutrino Observatory (**JUNO**) is designed to determine Neutrino Mass Ordering (**NMO**) with a large homogeneous liquid scintillator (LS) detector by measuring reactor electron antineutrino ($\bar{\nu}_e$) oscillations
- NMO sensitivity can be enhanced by a **combined analysis on reactor and atmospheric neutrino oscillations**
- Typical LS detectors are designed for low-energy neutrinos - ν_{atm} oscillations measurements using LS detectors has never been performed prior to this study
- Good capability of reconstructing atmospheric neutrinos are crucial
- **Different neutrino flavor exhibits different oscillation probabilities between two neutrino mass order, precise particle identification (PID) for atmospheric neutrinos is critical**
  - Signal Charged-Current (CC) vs Background Neutral-Current (NC)
  - Muon (anti)neutrinos vs electron (anti)neutrinos $\overset{(-)}{\nu}_\mu / \overset{(-)}{\nu}_e$
  - Neutrinos vs Antineutrinos $\nu/\bar{\nu}$
- **Demonstrate the capability of our ML approach in performing PID for atmospheric neutrinos**



2. Methodology

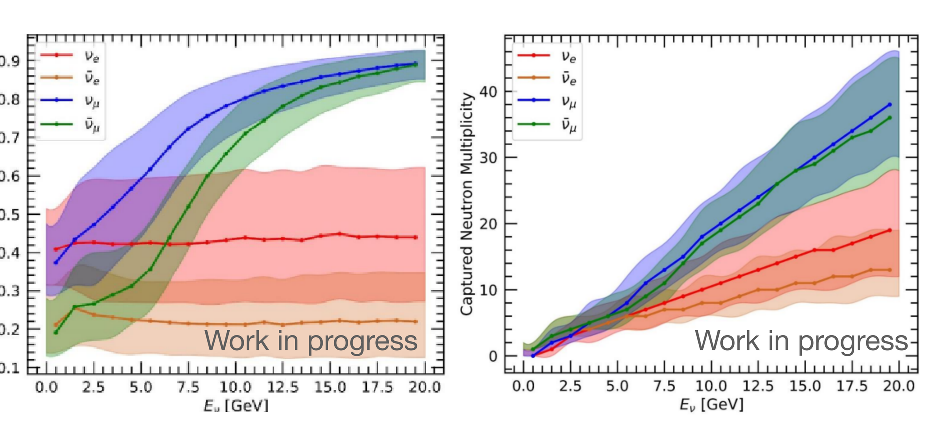
- Neutrino flavor can be determined by outgoing charged lepton from CC interactions
- Light seen by PMTs of an LS detector is a superposition of light generated from many points along the track
- Shape of light curve received by each PMT depends on angle w.r.t. track direction θ, track starting and stopping position, and particle type - different dE/dx
- Directly feeding full waveform from all PMTs are computationally expensive - features that reflects the waveforms are extracted to reduce data volume
- Features include first fit time (FHT), total PE (nPE), peak charge, peak time, and others such as median time and four moments of the waveform distributions (more details in Ref. [1])





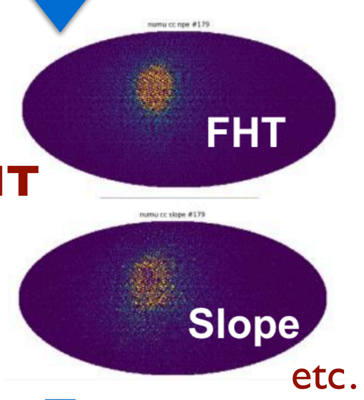
$\nu/\bar{\nu}$ Separation

- The difference between each CC interactions are also reflected by the final state hadrons from ν interactions
- Final state neutrons are captured by hydrogens in LS and emit a 2.2 MeV in ~ 200 μs, create delayed triggers after primary interactions
- Such events can be selected from delayed trigger with high efficiency
- The difference between $\nu/\bar{\nu}$ interactions can also be reflected by the hadronic energy fraction variable $Y_{ratio} = (E_\nu - E_{lepton})/E_\nu$, reflected by observables such as neutron multiplicity
- Expect to provide additional power especially for $\nu_e/\bar{\nu}_e$



Combing all PMTs

Pictures of PMT features



etc…

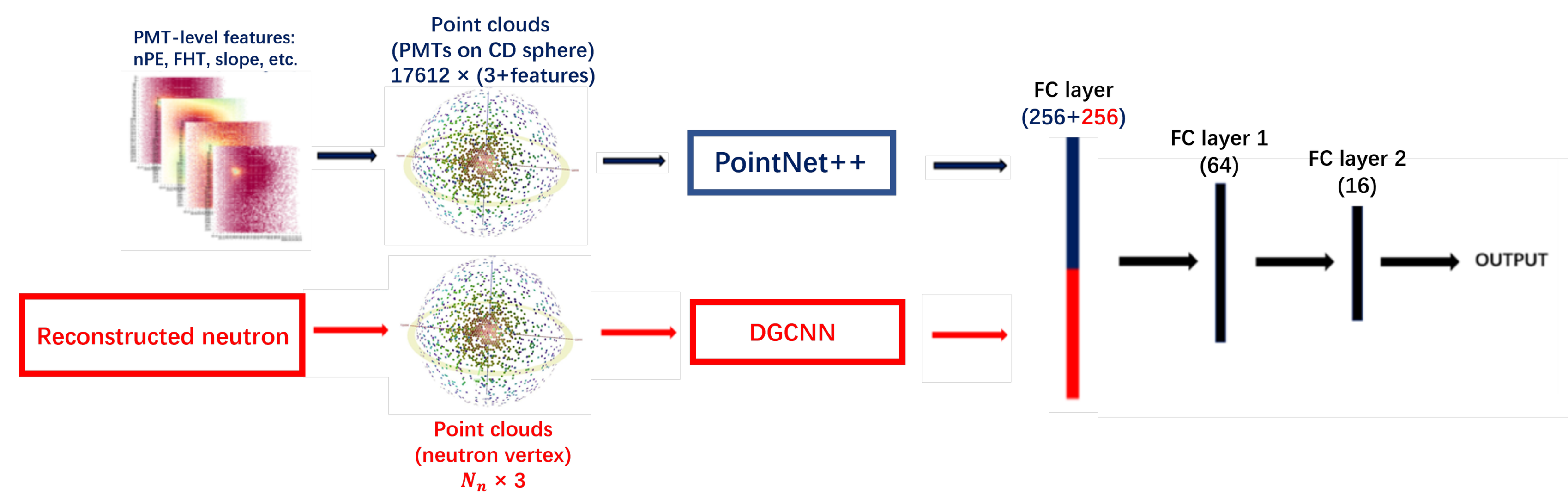
ML models (3-label)	ML models	ML models ($\nu_e/\bar{\nu}_e$)

Output Scores

3. Different strategies

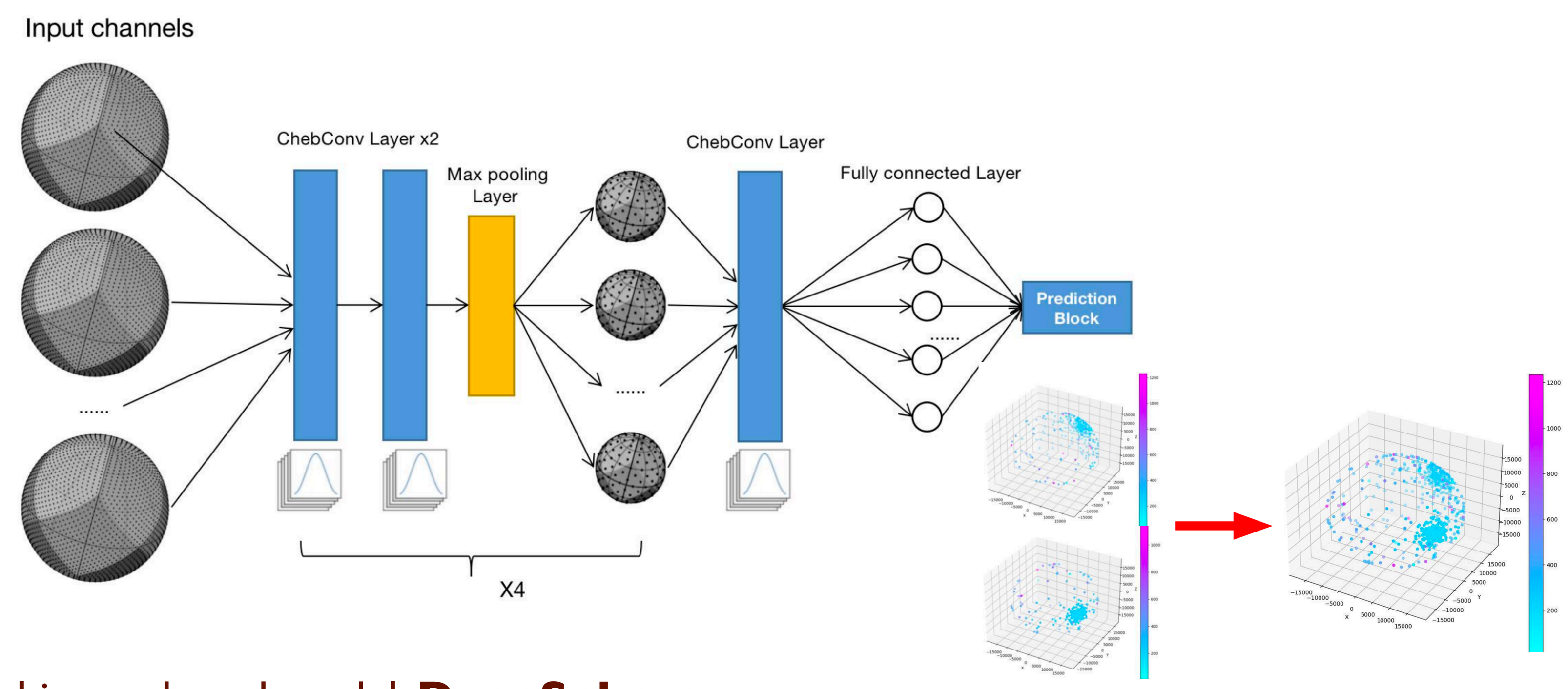
To process the 3-dimensional input of features from PMTs on a sphere, two strategies with different deep learning models are developed.

Strategy 1



- Point cloud-based model: **PointNet++, DGCNN**
- Features extracted from primary triggers are fed into the PointNet++
- For neutron capture candidates, taking 3D point clouds $N \times$ [x, y, z] as inputs to a separate DGCNN model
- Preserves multiplicity and spacial distributions of neutrons, minimise the information loss
- Concatenate with PointNet++ model with a FC layer for final output

Strategy 2



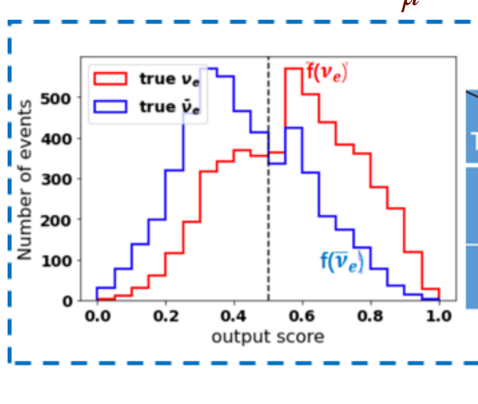
- Spherical image-based model: **DeepSphere**
- Designed to maintain rotational covariance
- Multiple neutron-candidate triggers are merged into one, from which FHT and nPE are extracted and feed into model together with primary trigger features
- All features are at the same PMT-level, fast and easy for model to handle the input

Both strategies uses all features from primary triggers and delayed triggers

2-step approach: 3-label classification (NC, $\overset{(-)}{\nu}_\mu$, $\overset{(-)}{\nu}_e$) followed by $\nu/\bar{\nu}$ classification, expect the ML models can each learn to specifically perform one classification tasks, either 3-label or 2-label.

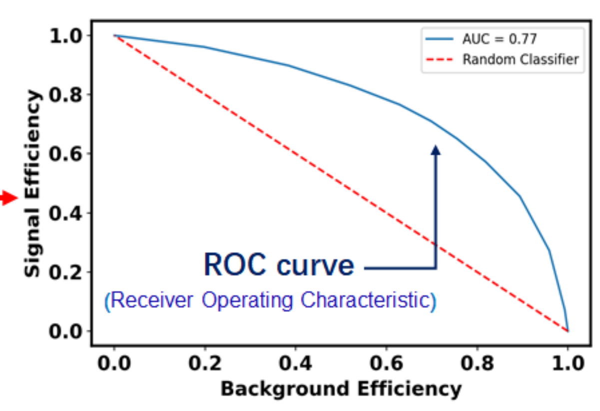
4. Evaluate model performance

- Training sample consist of ~25k events for all 5 categories considered (ν_μ-CC, $\bar{\nu}_\mu$-CC, ν_e-CC, $\bar{\nu}_e$-CC, NC), with flat energy spectrum [0, 20] GeV to avoid bias in model training
- Testing sample consist of ~5k events for all 5 categories
- ML models used by the two strategies are trained using labelled data, where the labels indicate either NC/ $\overset{(-)}{\nu}_\mu$/ $\overset{(-)}{\nu}_e$ for 3-label model, or $\nu/\bar{\nu}$ for 2-label model



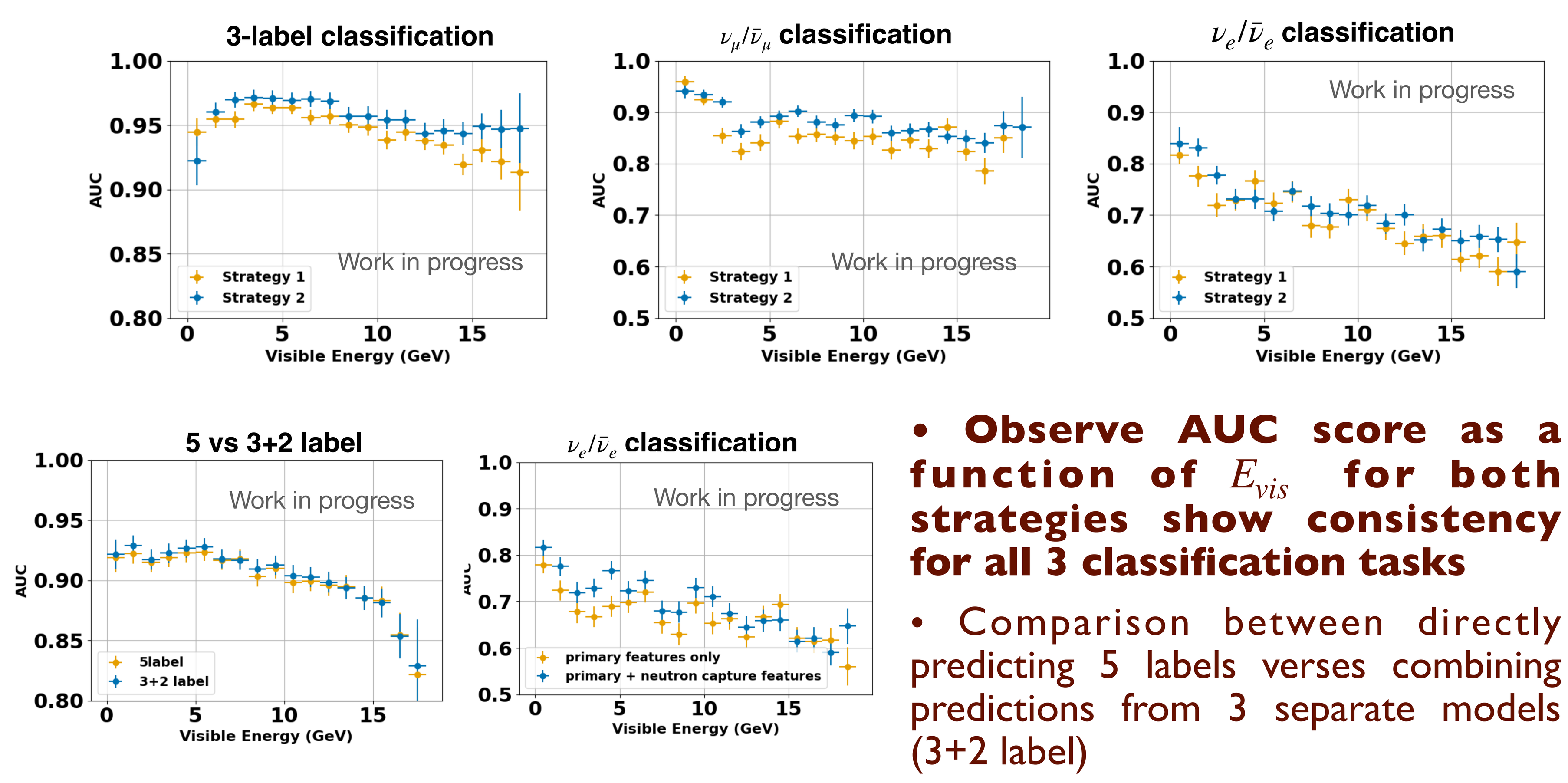
Confusion Matrix

Truth \ Pred	ν_e-like	$\bar{\nu}_e$-like
ν_e	$A=\int_{cut}^{1} f(\nu_e)$	$B=\int_{0}^{cut} f(\nu_e)$
$\bar{\nu}_e$	$C=\int_{cut}^{1} f(\bar{\nu}_e)$	$D=\int_{0}^{cut} f(\bar{\nu}_e)$



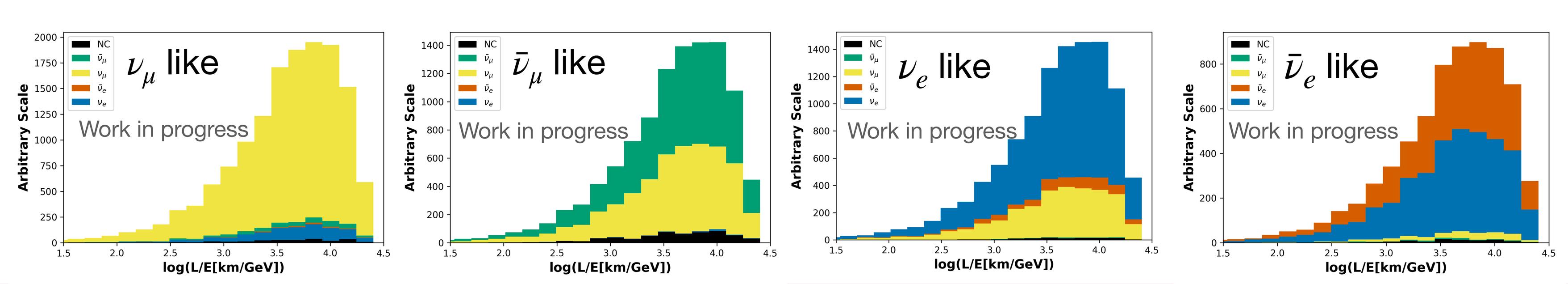
- The Area Under the Receiver Operating characteristic (ROC) Curve (**AUC**) are used to assess models' performances (optimising signal efficiency/background efficiency)
  - Does not depend on the choice of score cut
  - Not affected by class-imbalance in the dataset

5. Results



- **Observe AUC score as a function of E_{vis} for both strategies show consistency for all 3 classification tasks**
- Comparison between directly predicting 5 labels verses combining predictions from 3 separate models (3+2 label)

- The agreement suggests that the models considered are capable of directly classifying the 5 categories
- Assess the importance of additional neutron capture features by comparing results with/without these features for $\nu_e/\bar{\nu}_e$ classification
- **Efficiencies and purities can be tuned to obtain final selected sample**



References

[1] Zekun Yang et al. "First attempt of directionality reconstruction for atmospheric neutrinos in a large homogeneous liquid scintillator detector". Phys. Rev. D 109.5 (2024)

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