Poster ID #133

Machine learning-based particle identification of atmospheric neutrinos in JUNO

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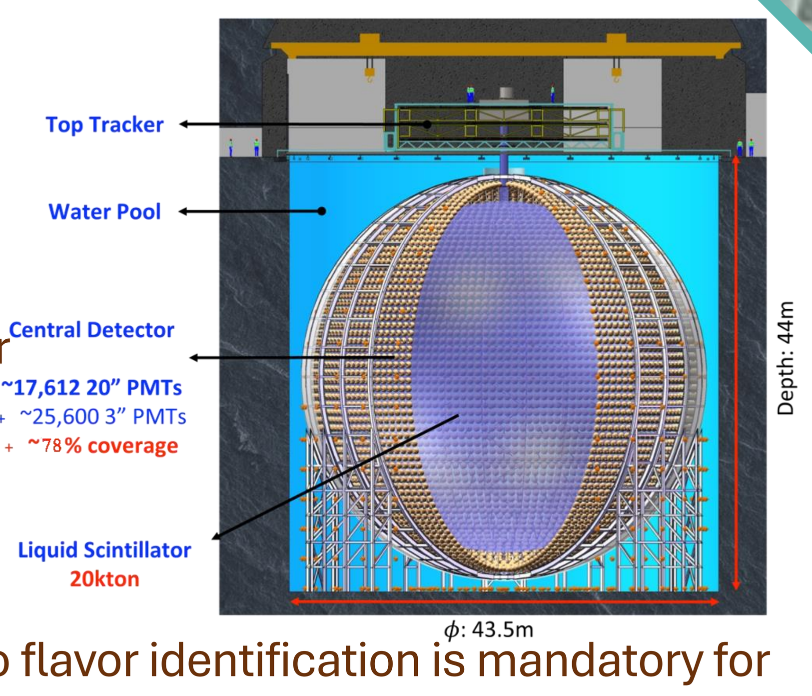
1. Overview

The Jiangmen Underground Neutrino Observatory (JUNO)

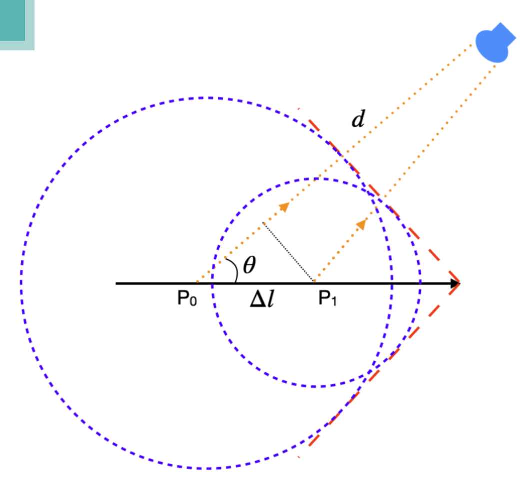
- **Main goal**: Determine Neutrino Mass Ordering (NMO) by measuring reactor Electron antineutrino ($\bar{\nu}_e$) oscillations with a large liquid scintillator (LS) detector
- **Enhanced Sensitivity**: Combined analysis of reactor and **atmospheric neutrino** oscillations can enhance JUNO's overall NMO sensitivity

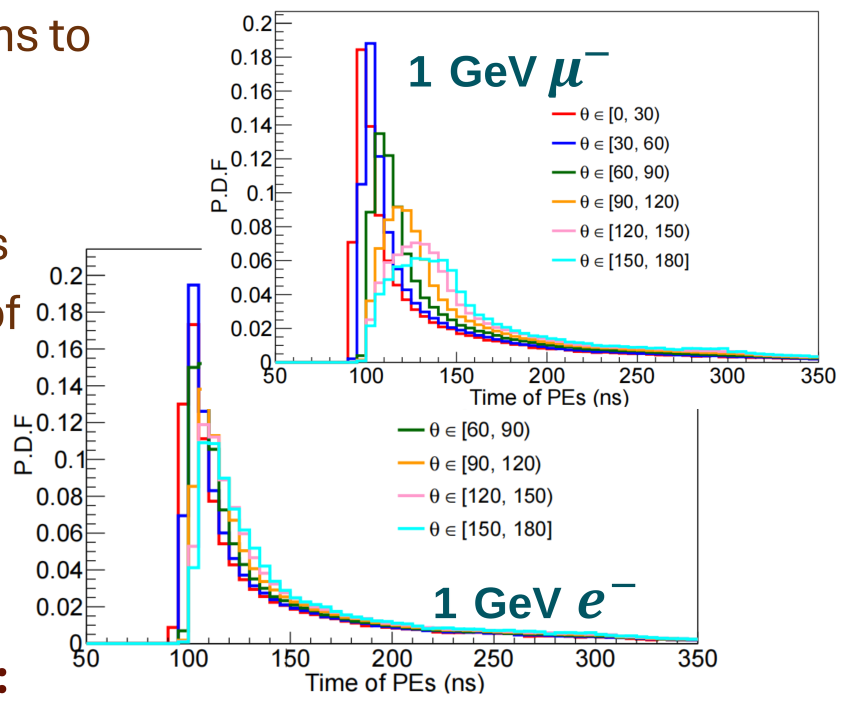


- **Neutrino Flavor Identification**: Neutrino flavor identification is mandatory for atmospheric neutrino oscillation measurements.
  - Muon (anti)neutrinos vs electron (anti)neutrinos vs neutral current (NC)
  - Neutrinos vs Antineutrinos ($\nu/\bar{\nu}$)
- **Innovation**: First low-energy neutrino (ν_{atm}) oscillation measurements using an LS detector

2. Methodology

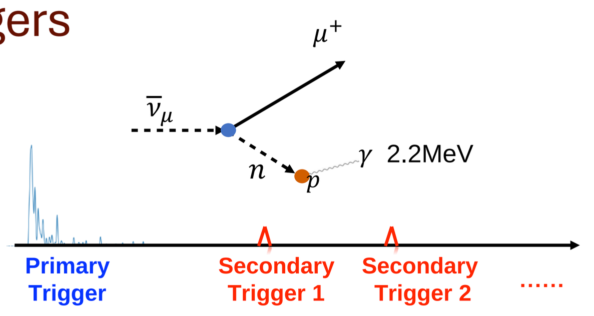
- Neutrino flavor can be determined by outgoing charged lepton from charge current (CC) interactions
- Light received by a PMT in the LS detector is the superposition of light from points along the track
- Light received by a PMT evolves as a function of time depends upon its angle w.r.t. the particle direction, position, visible energy, and **type (dE/dx)**.
- Features are extracted from PMT waveforms to reflect the event topologies.
- 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])

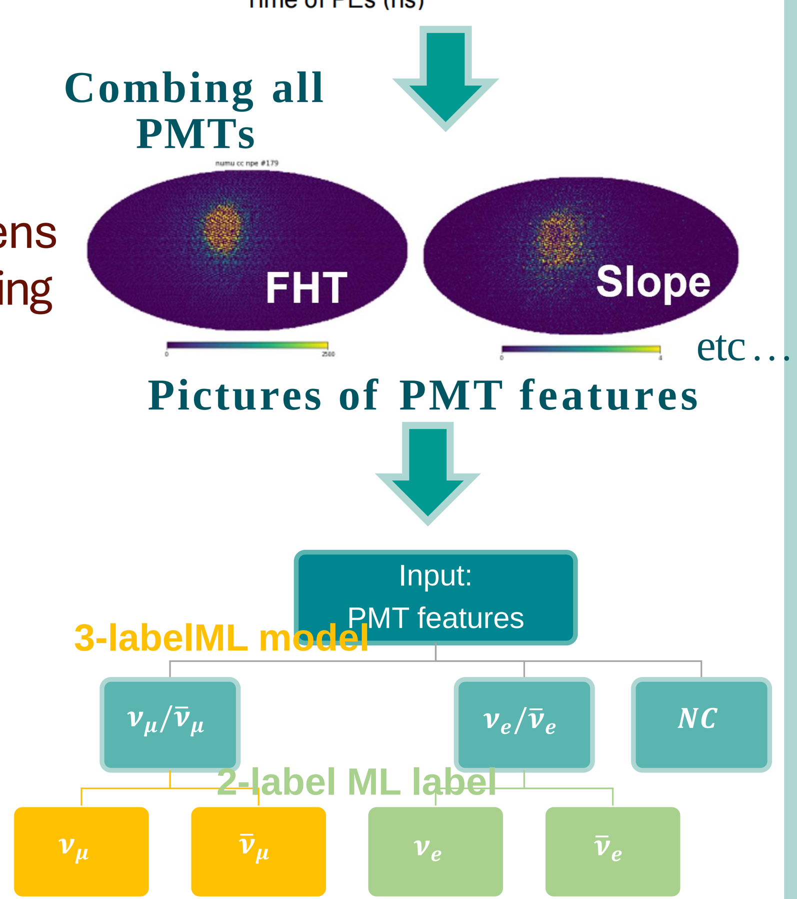


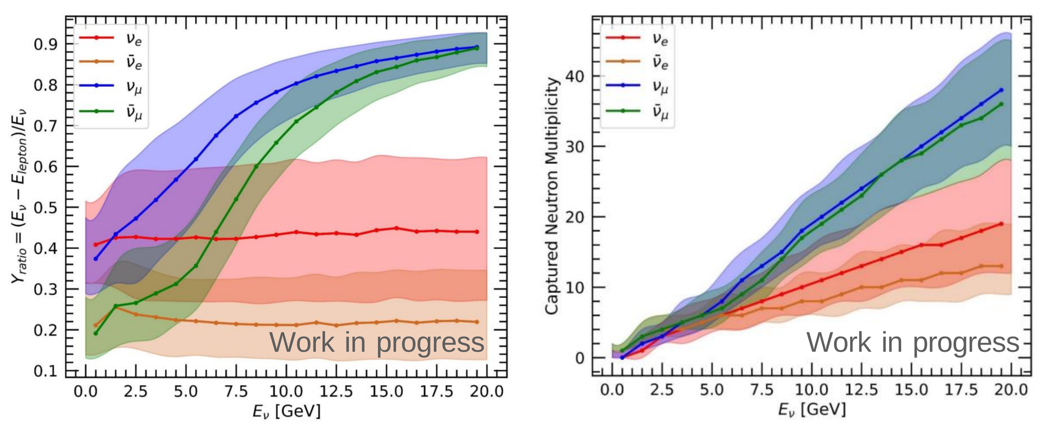


$\nu/\bar{\nu}$ Separation

- **Differences between ν and $\bar{\nu}$ interactions:**
  - The hadronic energy fraction $Y_{vis} = (E_\nu - E_{lepton})/E_\nu$, reflected by PMT waveforms
  - Neutron multiplicities on average
    - Final state neutrons captured by hydrogens in LS emits a 2.2 MeV photon in ~ 200 μs, creating secondary triggers



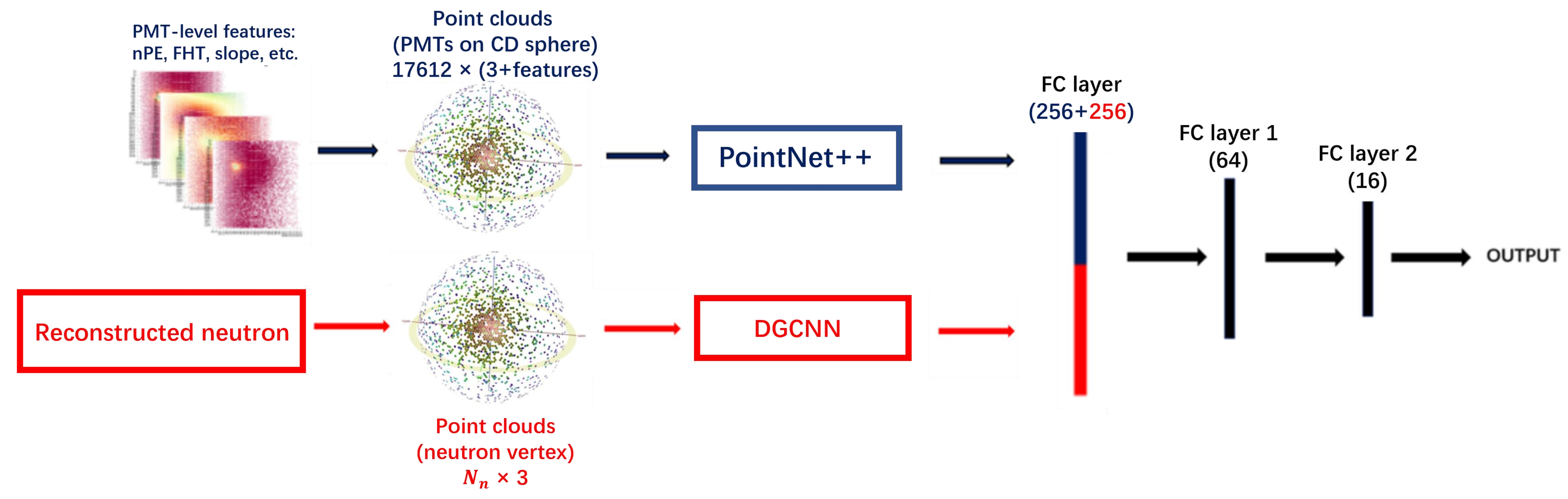




3. Different strategies

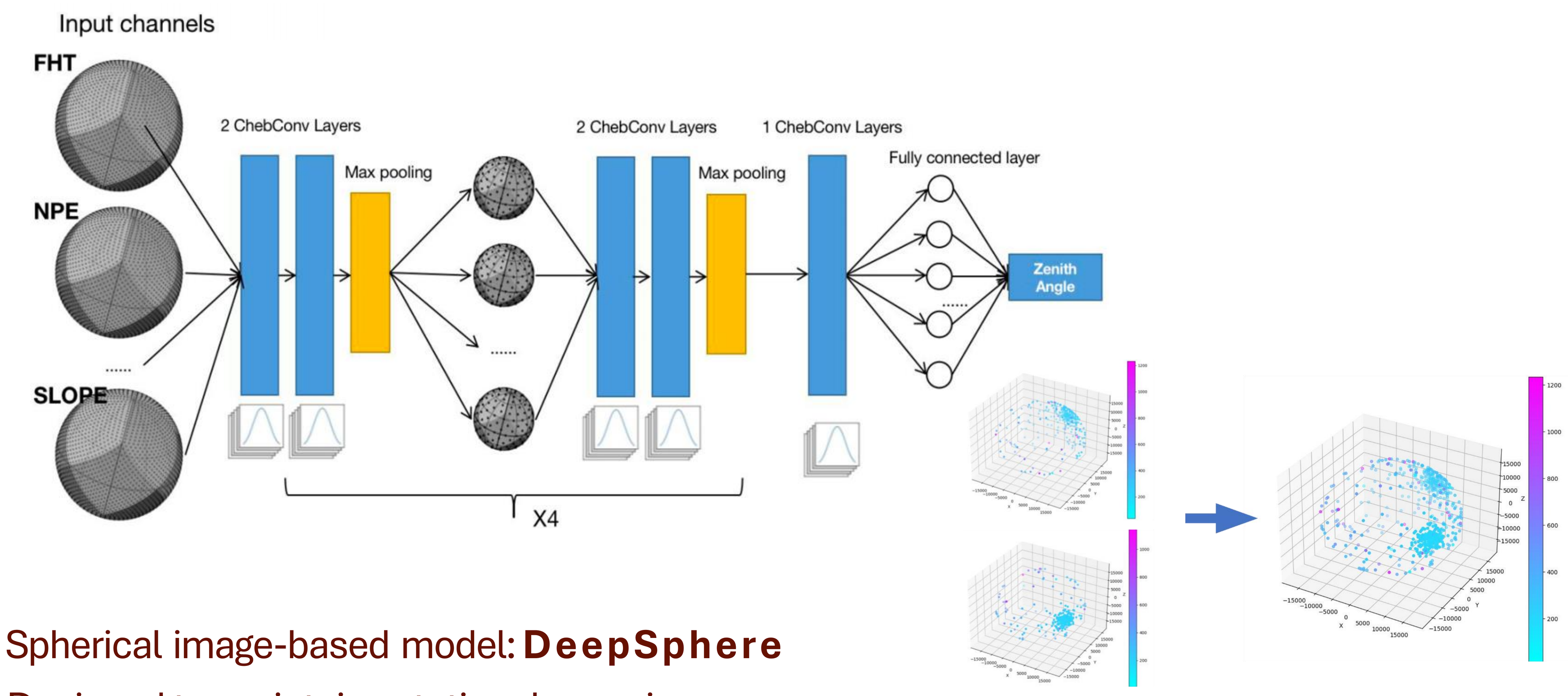
To process primary and secondary triggers, two strategies with different deep learning models are developed.

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, minimize the information loss
- Concatenate with PointNet++ model with an FC layer for final output

Strategy 2



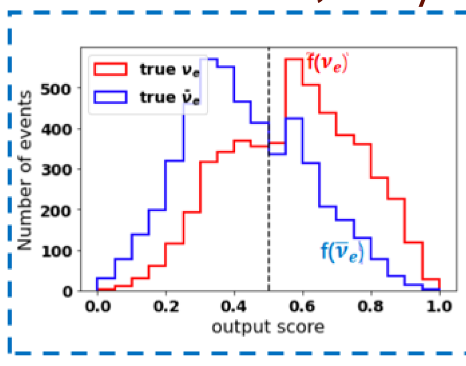
- Spherical image-based model: **DeepSphere**
- Designed to maintain rotational covariance
- Multiple neutron-candidate triggers are merged into one, from which FHT and nPE are extracted and fed into the model together with primary trigger features
- All features are at the same PMT level, fast and easy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

Both strategies use all features from primary triggers and secondary triggers

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

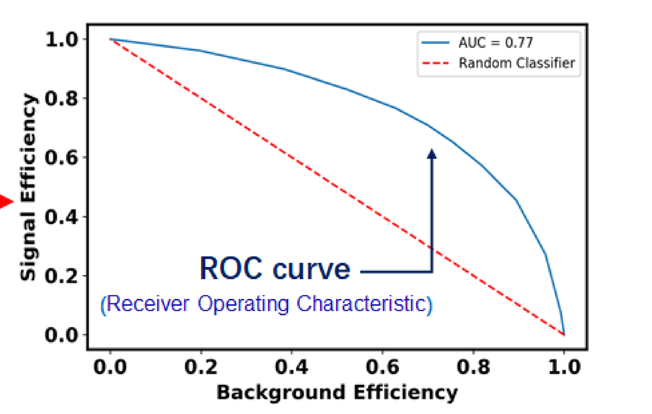
4. Evaluate model performance

- Training sample: ~25k events for all 5 categories (ν_μ-CC, $\bar{\nu}_\mu$-CC, ν_e-CC, $\bar{\nu}_e$-CC, NC), with a flat energy spectrum [0, 20] GeV to avoid bias in model training
- Testing sample: ~5k events for all 5 categories
- ML models are trained with labeled data, indicating either NC/$\overset{(-)}{\nu}_\mu$/$\overset{(-)}{\nu}_e$ for the 3-label model, or $\nu/\bar{\nu}$ for the 2-label model



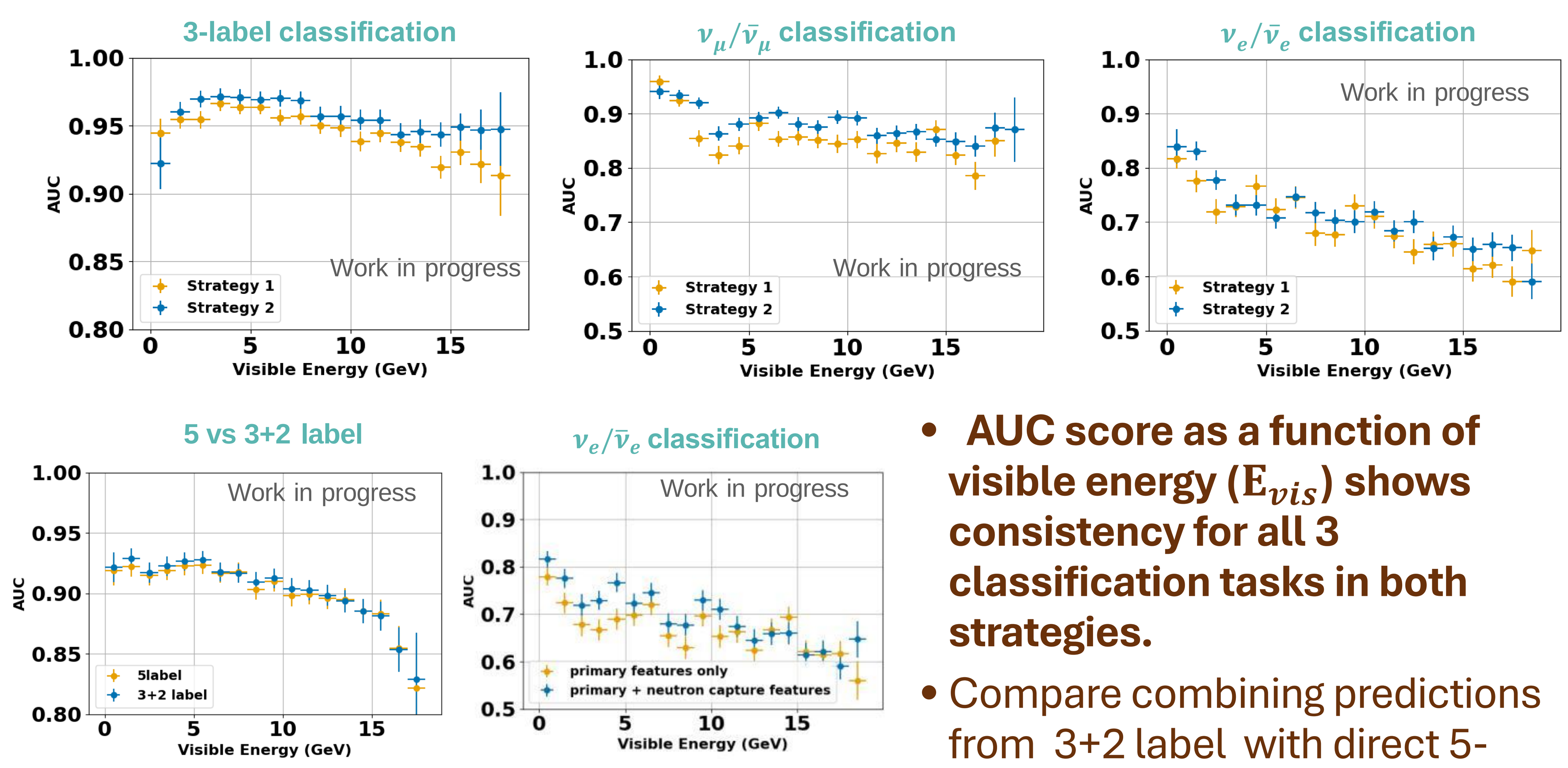
Confusion Matrix

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=$\int_{0}^{cut} f(\bar{\nu}_e)$



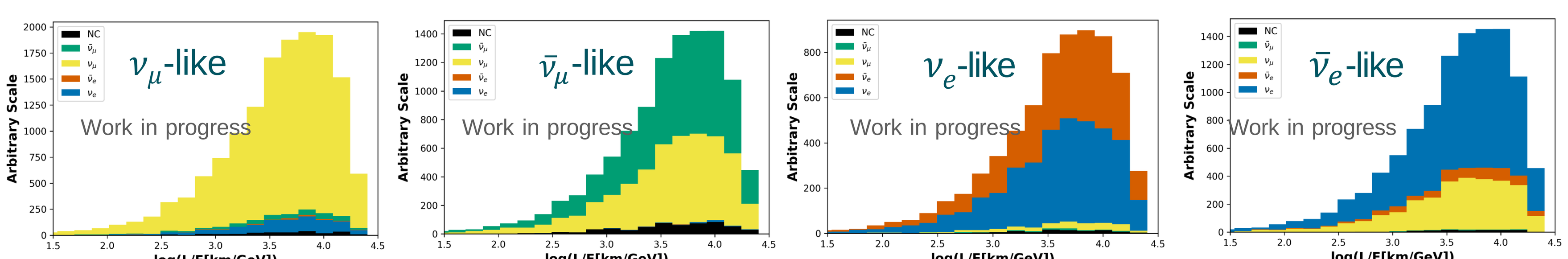
- The Area Under the Receiver operating characteristic (ROC) Curve (**AUC**) is used to assess models' performances (optimizing signal efficiency/background efficiency)
  - Does not depend on the choice of score cut
  - Not affected by class imbalance in the dataset

5. Results



- **AUC score as a function of visible energy (E_{vis}) shows consistency for all 3 classification tasks in both strategies.**
- Compare combining predictions from 3+2 label with direct 5-label prediction

- The agreement suggests that the models can directly classify 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)