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Neutrino Classification Through Deep Learning

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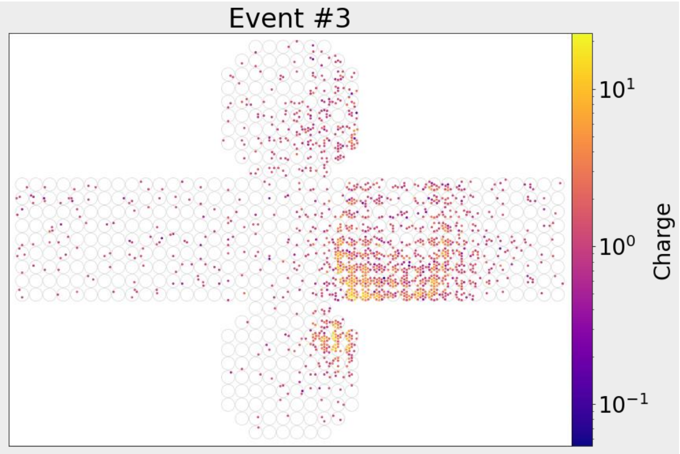
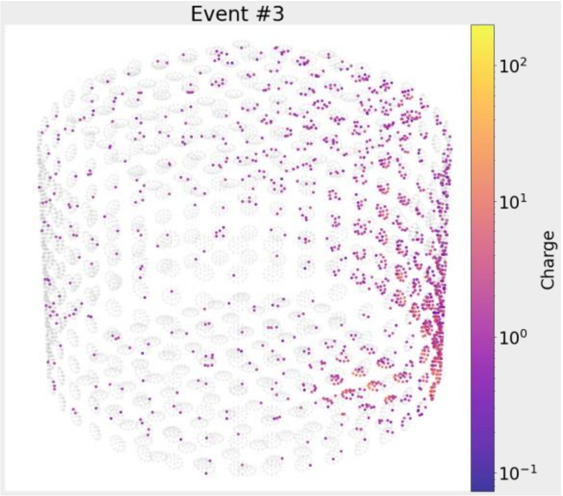
Introduction

Objective: Apply **deep learning** to the process of **classifying particles** involved in an event amid the Hyper-Kamiokande Project development and determine **which works best**





Data

- Simulated with WCSim
- IWCD Tank (8m tall, 10m diameter, 536 mPMTs)
- Single ring events
- 3 classes: gamma/electron/muon

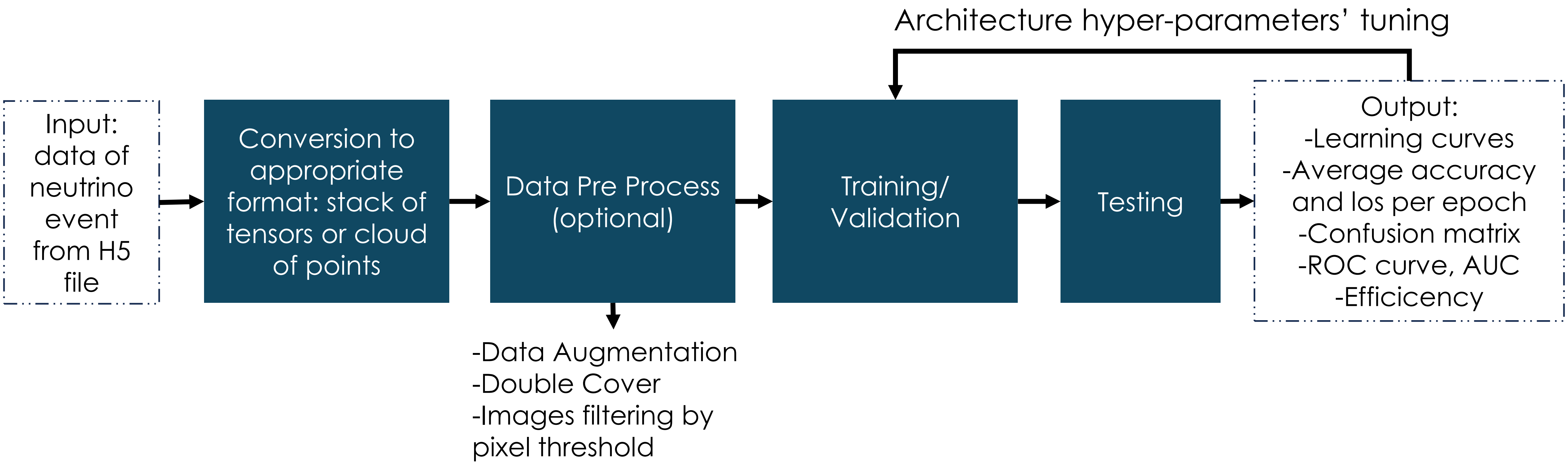
Database	Class	# Events
CADS	Gamma Electron Muon	9k to 3M per particle
Cedar	Gamma Electron Muon	~8 M ~8 M ~3 M

Methodology

4 Deep learning architectures:

- PointNet
- VGG19
- ResNet50
- Vision Transformer

VGG19, ResNet50, Vision Transformer: CNN based



Developed Models

- VGG19
- ResNet50 → **Cedar dataset**
- PointNet

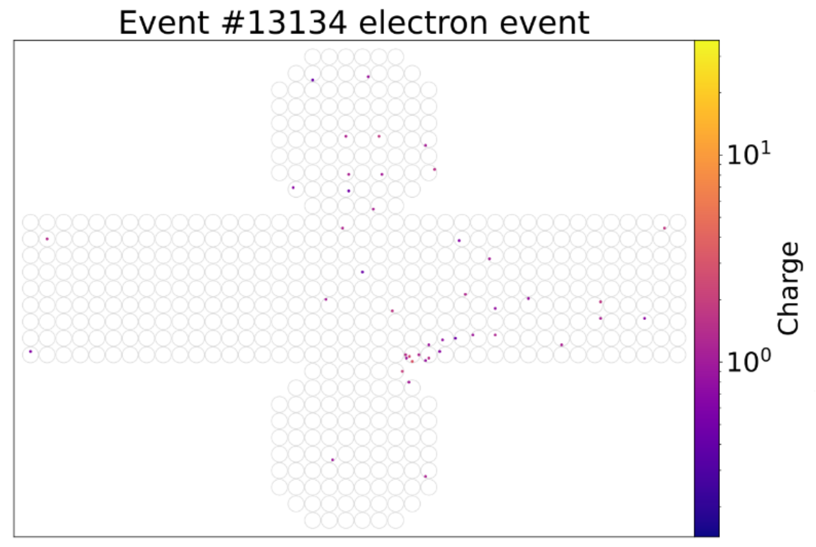
3 classes: gamma, electron, muon → 9k per class

- Vision Transformer Unfiltered Data

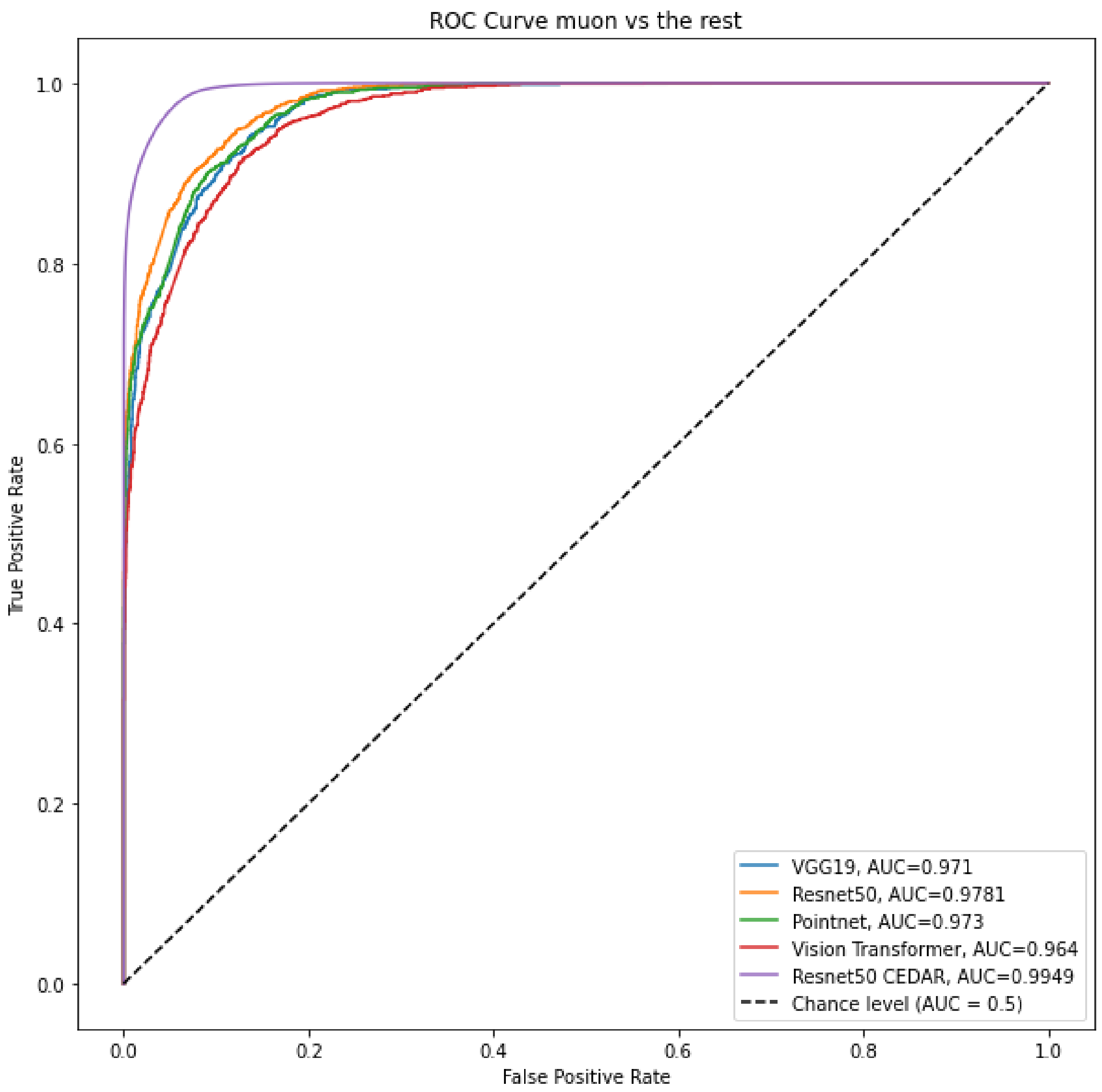
2 classes: muon, not muon → 9k, 18k, respectively

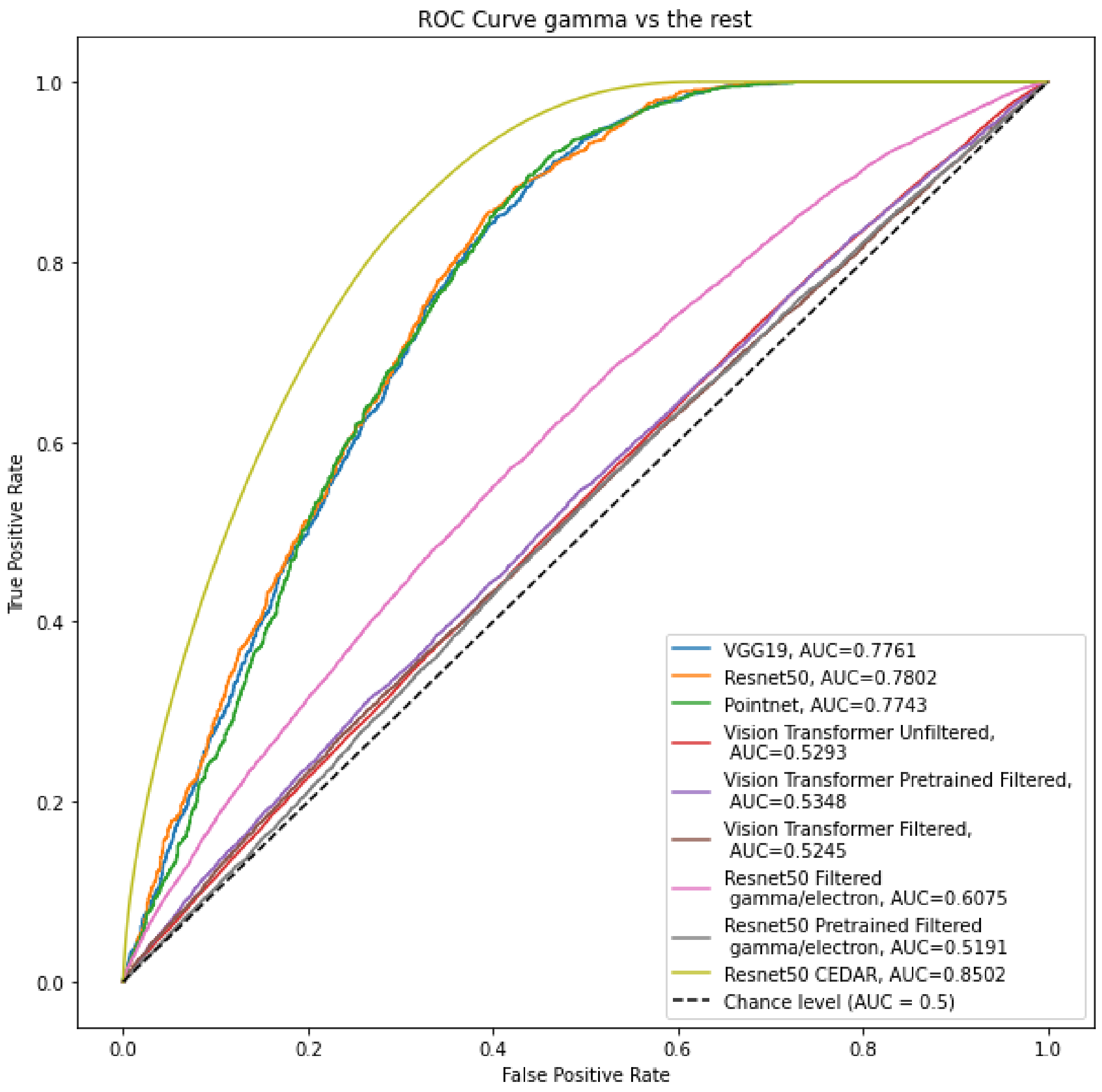
- Vision Transformer Unfiltered Data
- Vision Transformer Filtered Data
- Vision Transformer Pretrained Filtered Data
- ResNet50 Filtered Data
- ResNet50 Pretrained Filtered Data

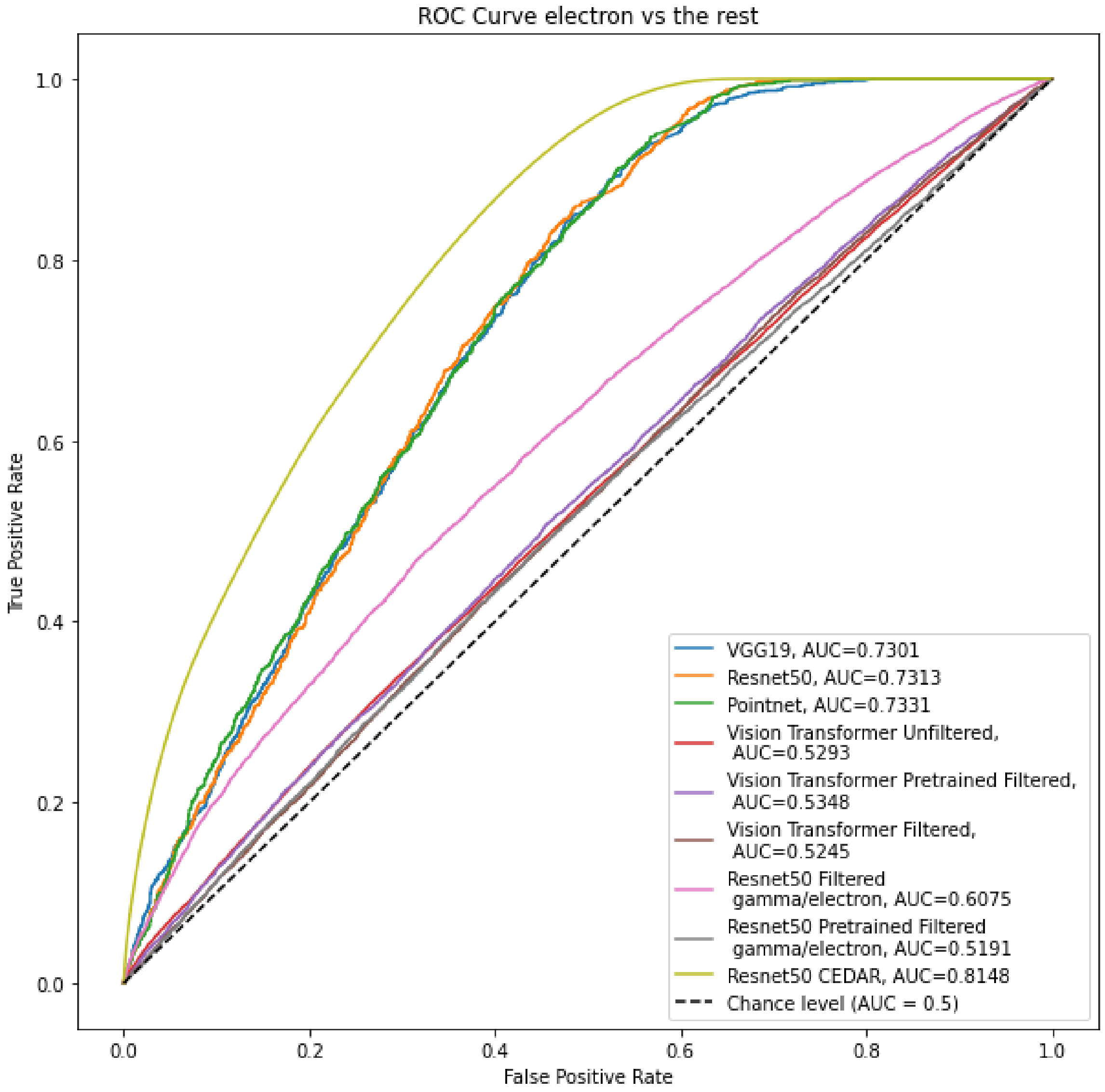
2 classes: electron, gamma → 30k, 300k per class



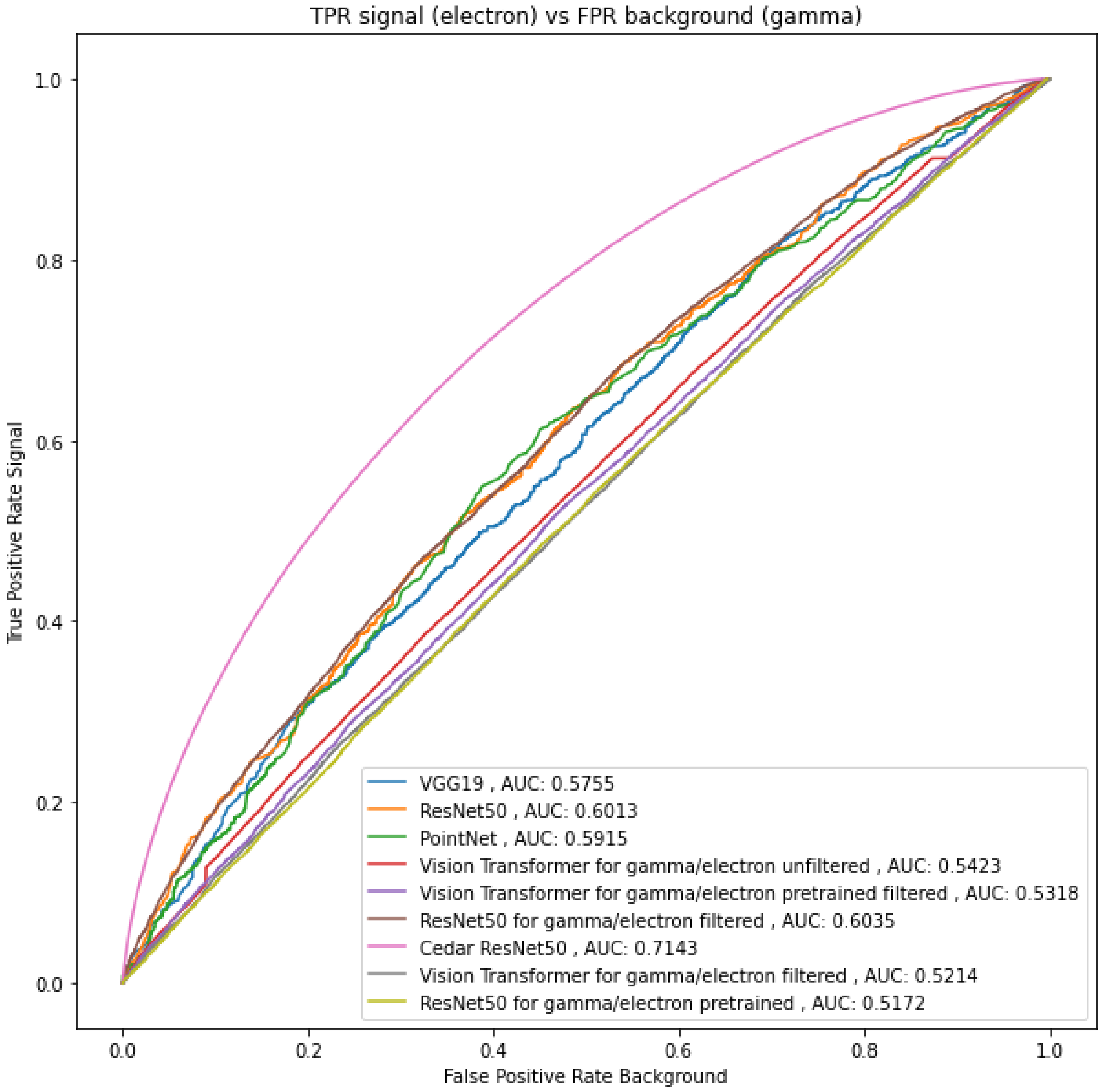
Results


ROC Curve muon vs the rest
True Positive Rate
False Positive Rate
VGG19, AUC=0.971
Resnet50, AUC=0.9781
Pointnet, AUC=0.973
Vision Transformer, AUC=0.964
Resnet50 CEDAR, AUC=0.9949
Chance level (AUC = 0.5)


ROC Curve gamma vs the rest
True Positive Rate
False Positive Rate
VGG19, AUC=0.7761
Resnet50, AUC=0.7802
Pointnet, AUC=0.7743
Vision Transformer Unfiltered, AUC=0.5293
Vision Transformer Pretrained Filtered, AUC=0.5348
Vision Transformer Filtered, AUC=0.5245
Resnet50 Filtered gamma/electron, AUC=0.6075
Resnet50 Pretrained Filtered gamma/electron, AUC=0.5191
Resnet50 CEDAR, AUC=0.8502
Chance level (AUC = 0.5)


ROC Curve electron vs the rest
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
VGG19, AUC=0.7301
Resnet50, AUC=0.7313
Pointnet, AUC=0.7331
Vision Transformer Unfiltered, AUC=0.5293
Vision Transformer Pretrained Filtered, AUC=0.5348
Vision Transformer Filtered, AUC=0.5245
Resnet50 Filtered gamma/electron, AUC=0.6075
Resnet50 Pretrained Filtered gamma/electron, AUC=0.5191
Resnet50 CEDAR, AUC=0.8148
Chance level (AUC = 0.5)

Efficiency plot for electron (signal) vs gamma (background)



Therefore, after training 4 architectures and producing 9 models…

- ResNet50 provides the best results while also consuming the less computational resources → Greatest AUC for all applications in comparison to other models, stable efficiency for all classes.
- VGG19 and PointNet come close to ResNet50's results →The resources needed double or triple the time of ResNet50.
- Vision Transformer gave the poorest results → Improved by using a pretrained model
- Comparing with WatChMaL AUC 0.71 vs 0.77 and 0.74 (employing basic and all cuts) [1]
- The more data we use the better the results.

[1] N. Prouse, "Machine Learning for Reconstruction (& detector simulation & calibration)," presented at the HK Collaboration Meeting, Kamioka Research Complex, Oct. 24, 2023

Future Work

- Test other deep learning methods with similar functioning principle to ResNet50: DenseNet, InceptionNet.
- Train VGG19 and PointNet with the largest dataset if posible.
- Train Vision Transformer from scratch using the Cedar dataset.
- Employ other Vision Transformer methods such as BEiT.
- Test traditional machine learning techniques (extract features from the data and use them to train and test a classifier).

- Romo-Fuentes et al. paper in progress

Thank you for your attention

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