Probing highly collimated photon-jets at the LHC with deep learning

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Collaborators:

Xiaocong Ai, Shih-Chieh Hsu and Ke Li, **arXiv:2401.15690**

A.Hammad, P. Ko, Myeonghun Park, ***JHEP* 09 (2024) 166**

29th Mini-workshop on the frontier of LHC

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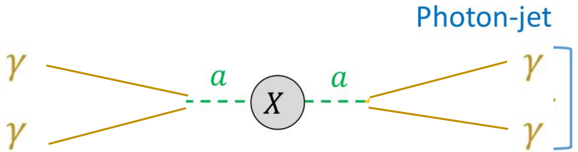
What is highly collimated photon-jets ?

1. Definition of "**photon-jet**" : Grouping of collimated photons
2. How to generate photon-jet?

(1) Cascade decay: heavy resonance (X) → light resonances (a) → photons

(2) Boosted light resonances (a) decaying into photons leads to a photon-jet

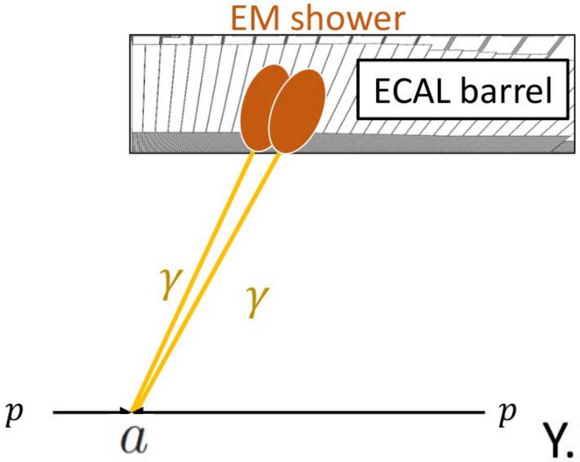


For $m_X = 125$ GeV and sub-GeV m_a,
a photon-jet leads to one EM cluster

E.g. for $X \to aa \to 4\gamma$,

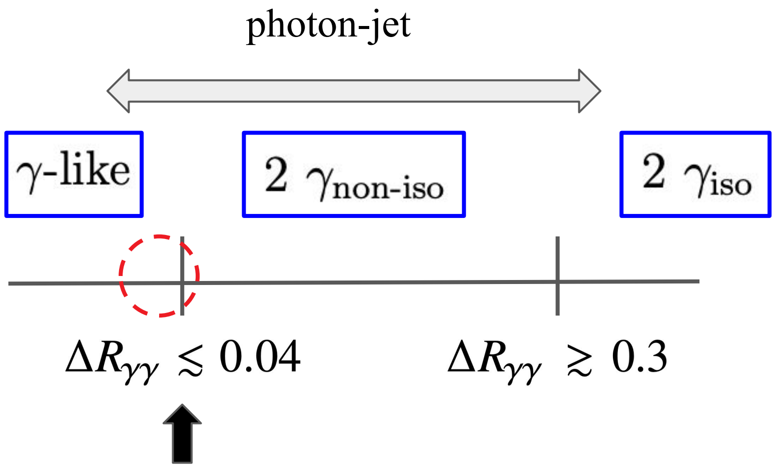
$$\Delta R_{\gamma\gamma} \sim 4 \cdot \frac{m_a}{m_X} = 0.015 - 0.035$$

$(\because \Delta R_{\gamma\gamma} \sim \frac{2}{\gamma_a}$, where γ_a : Lorentz factor of $a)$



Y.Kano

Two isolated photons, OR a photon jet, OR a single photon-like ?



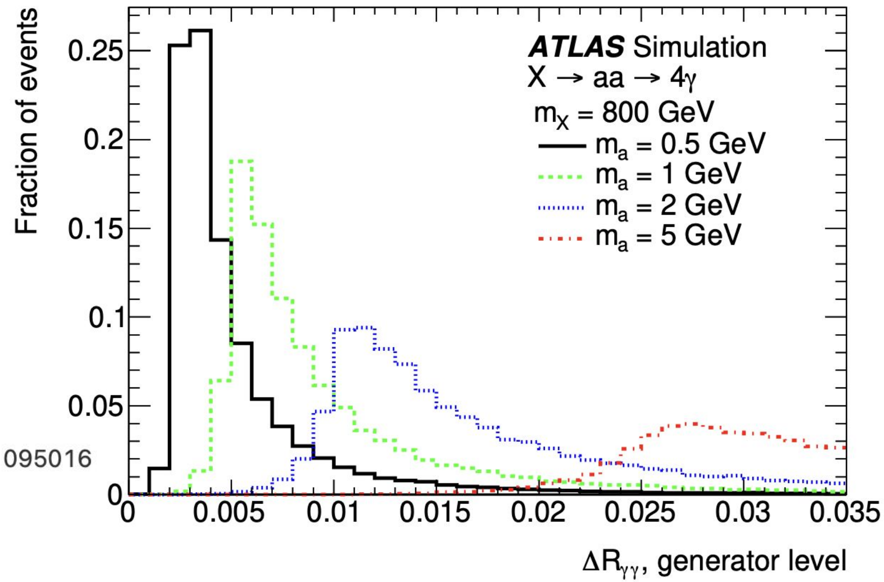
ATLAS existing triggers

cannot distinguish them !

Phys.Rev.D 104 (2021) 9, 095016

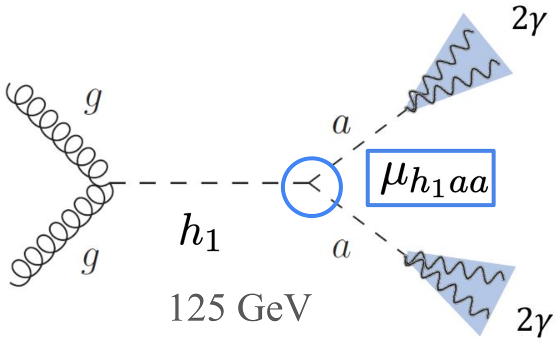
JHEP 10 (2021) 012

Phys.Rev.D 99 (2019) 1, 012008



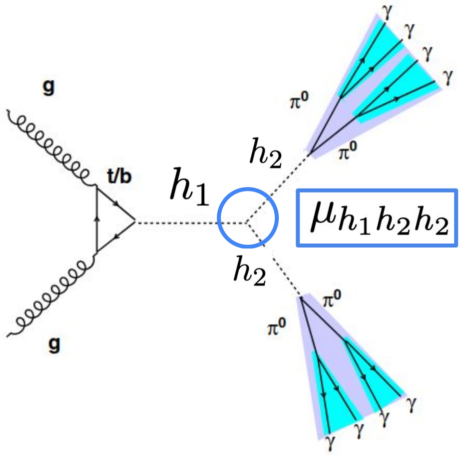
Topology of signal signatures

Photon-jet with 2 photons



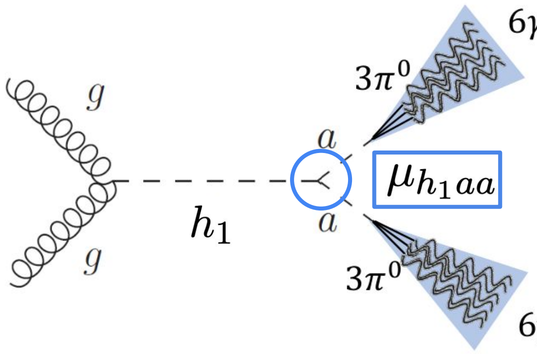
Phys.Rev.D 99 (2019) 1, 012008

Photon-jet with 4 photons



Phys.Rev.D 93 (2016) 7, 075013

Photon-jet with 6 photons



Phys.Rev.D 99 (2019) 1, 012008

Xiaocong Ai, Shih-Chieh Hsu and Ke Li, **CT Lu**
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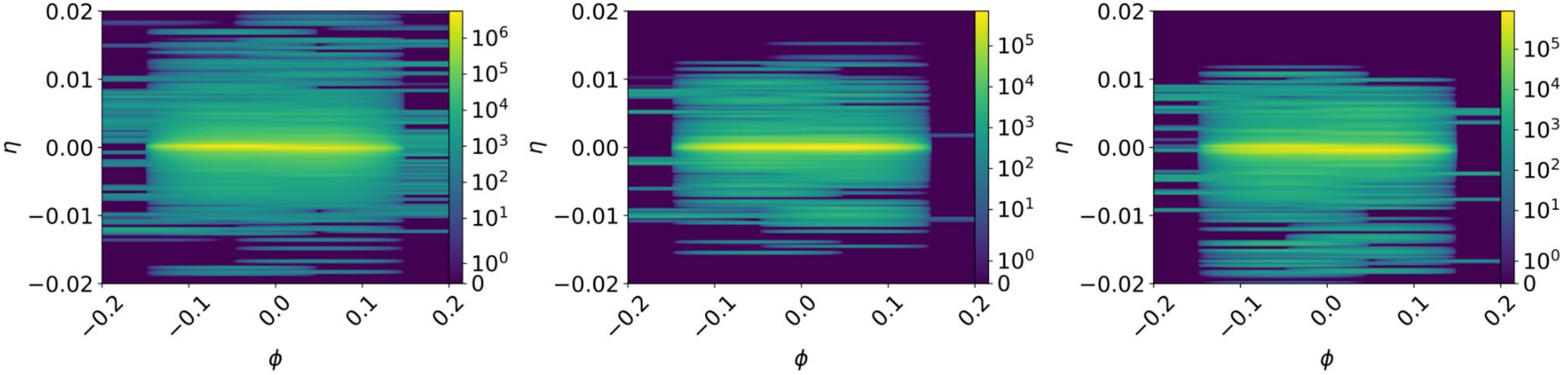
Contents

Photon-jet Identification with Deep Learning

ATLAS-like ECAL with EM showers simulated using GEANT4

100,000 events
for each sample

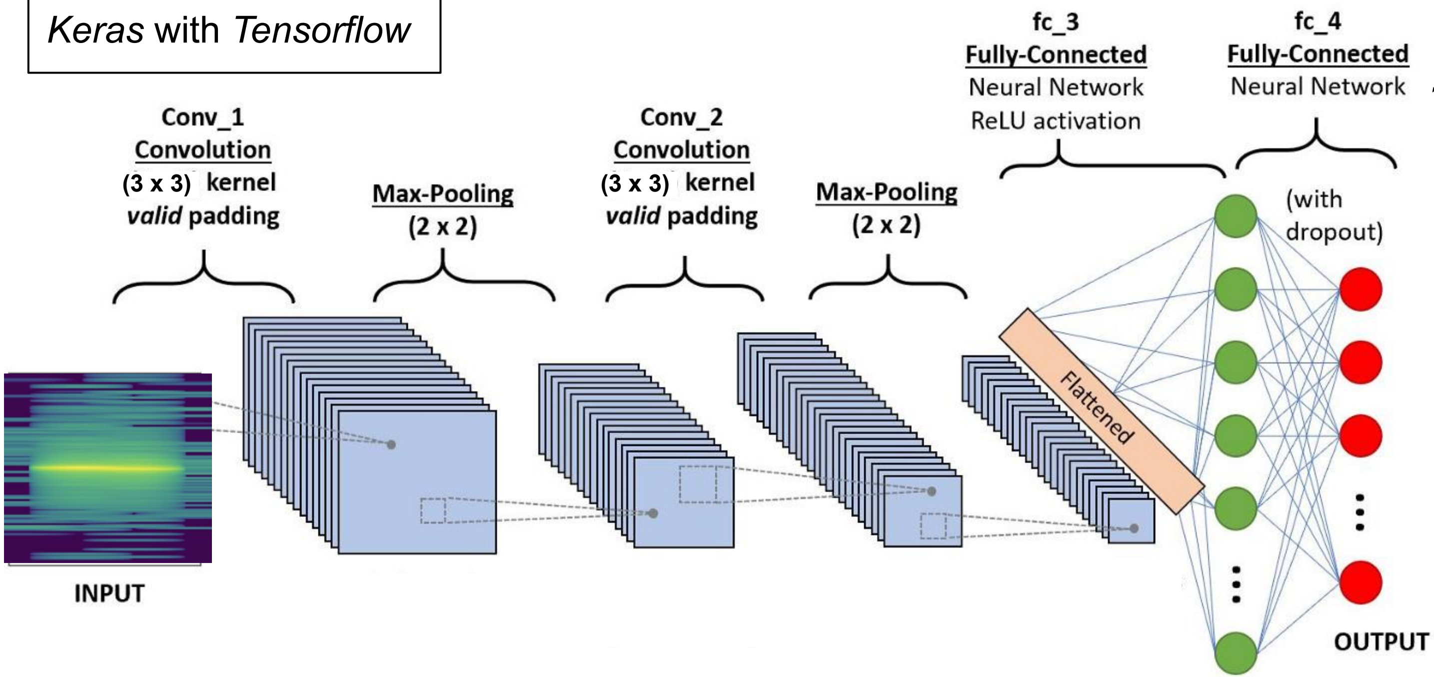
The deposited energy per cell at the 1st layer of the ECAL in the range of [40, 250] GeV :



(a) $a \to \gamma\gamma$ ($m_a = 1$ GeV) (b) γ (c) π^0

Convolutional Neural Networks (CNN)

Keras with *Tensorflow*



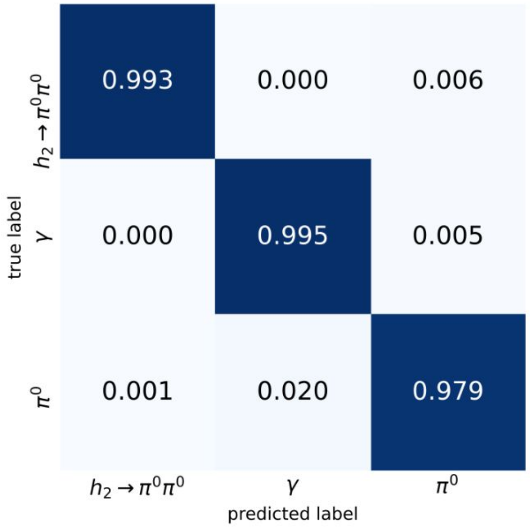
softmax activation

32 nodes

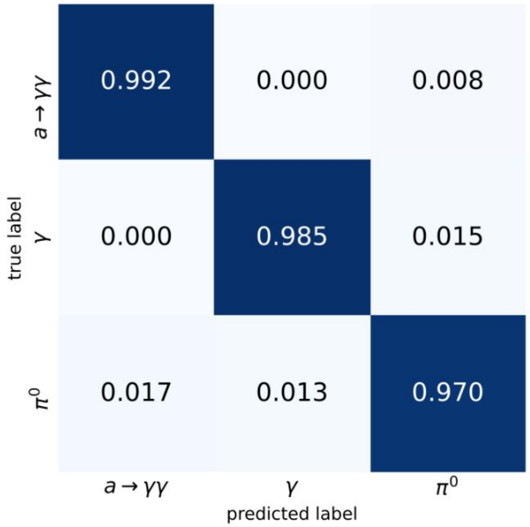
70% → training
30% → test

Convolutional Neural Networks (CNN)

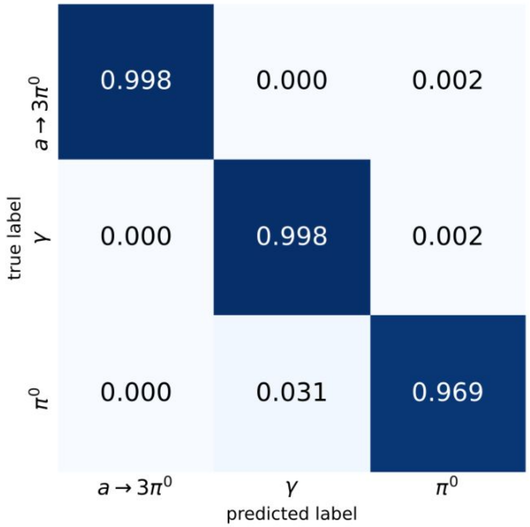
The normalized confusion matrix



(a) $h_2 \to \pi^0\pi^0$



(b) $a \to \gamma\gamma$



(c) $a \to \pi^0\pi^0\pi^0$

Particle Flow Networks (PFN)

1. Developed by Komiske et al., Energy Flow Networks: Deep Sets for Particle Jets, JHEP 01, 121 (2019)
2. Input: A jet represented in point-cloud form (i.e. an unordered set of feature vectors)
3. Output: A vector of probabilities for classification.
4. PFNs are able to model any permutation-invariant function on a point cloud.
5. PFNs cannot directly take our ECAL images as input, so we transform the array of each sampling layer into an unordered set of "points" (feature vectors).

Particle Flow Networks (PFN)

$$\mathrm{PFN}(\mathcal{C}) = F\left(\sum_{\vec{p}\in\mathcal{C}} \Phi(\vec{p})\right)$$

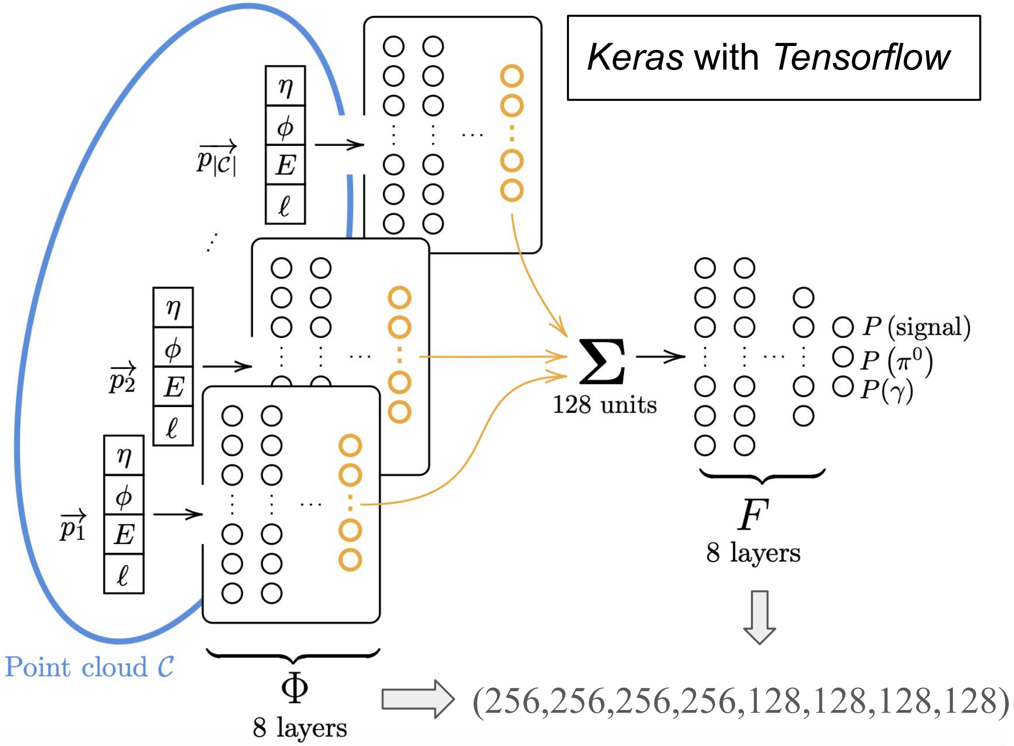
F and Φ are vector functions approximated by DNNs.

特征嵌入函数 (Φ)

$$\Phi : \mathbb{R}^4 \to \mathbb{R}^{128}$$

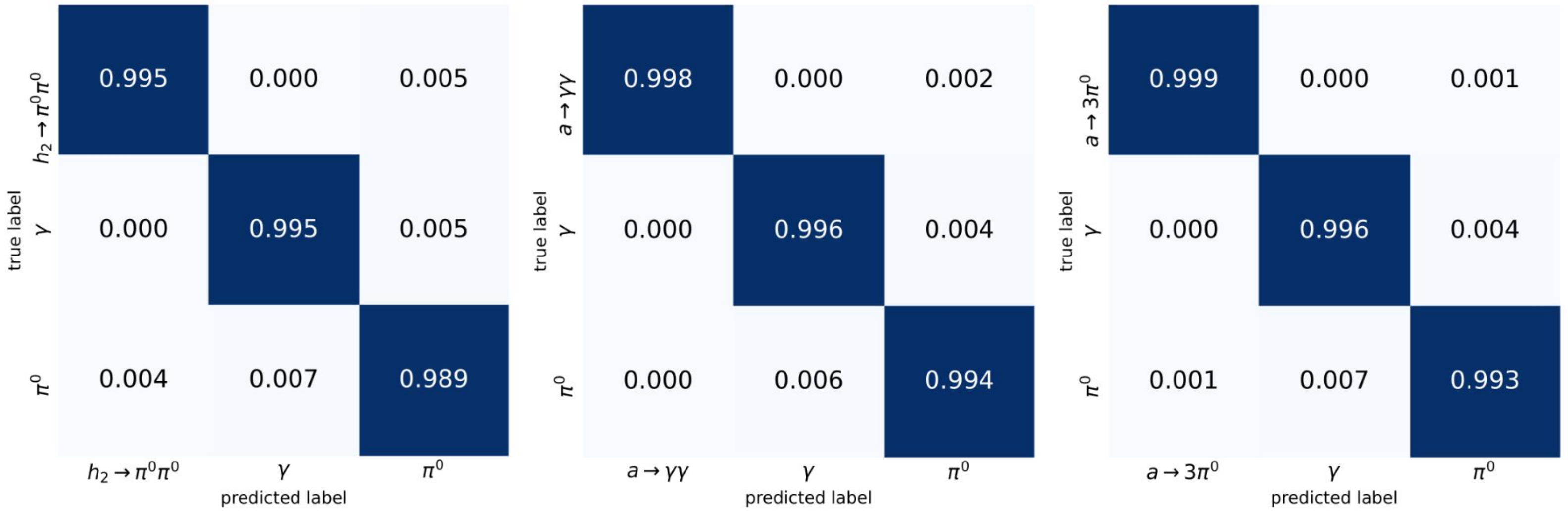
聚合函数 (F)

$$F : \mathbb{R}^{128} \to \mathbb{R}^3$$

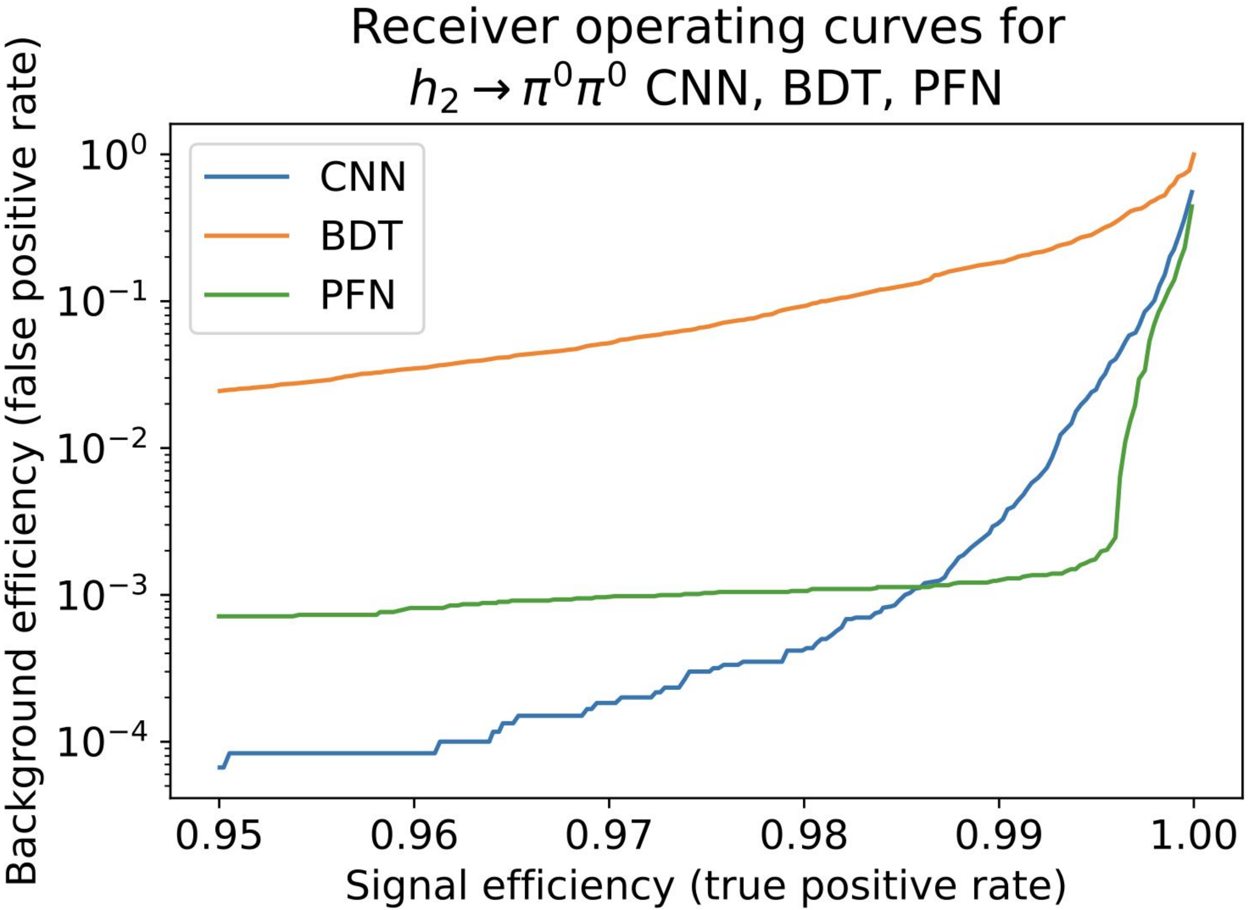


Particle Flow Networks (PFN)

The normalized confusion matrix

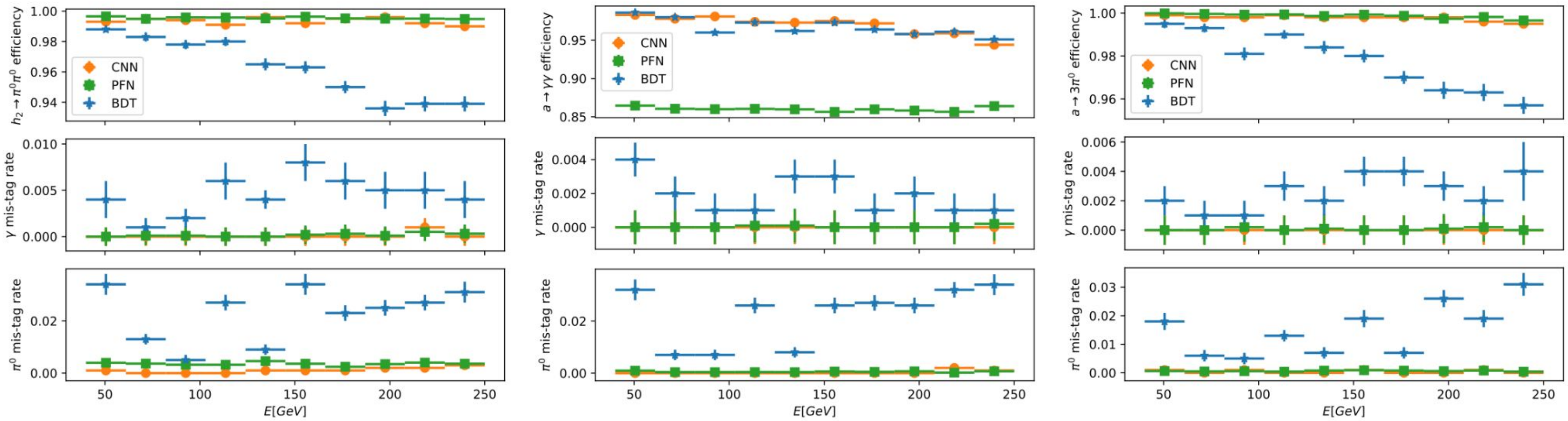


(a) $h_2 \to \pi^0\pi^0$ (b) $a \to \gamma\gamma$ (c) $a \to \pi^0\pi^0\pi^0$



Receiver operating curves for
$h_2 \rightarrow \pi^0\pi^0$ CNN, BDT, PFN
CNN
BDT
PFN
Background efficiency (false positive rate)
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
0.95
0.96
0.97
0.98
0.99
1.00
Signal efficiency (true positive rate)

Comparison of performance among CNN and BDT



(a) $h_2 \to \pi^0\pi^0$ (b) $a \to \gamma\gamma$ (c) $a \to \pi^0\pi^0\pi^0$

Shower shape variables : *Eur.Phys.J.C* 79 (2019) 3, 205

Gradient Boosted Decision Trees (BDT)

$$R_{\mathrm{had}_1},\ R_{\mathrm{had}},\ R_\eta,\ \omega_{\eta 2},\ R_\phi,\ \omega_{s\,3},\ \omega_{s\,\mathrm{tot}},\ f_{\mathrm{side}},\ \Delta E_s,\ E_{\mathrm{ratio}},\ f_1.$$

Contents

Simulation :

Feynrules : generate the UFO model files

MadGraph5 : generate the signal and background events

PYTHIA 8 : parton showering and hadronization

Basic event selections

GEANT4 : ATLAS-like ECAL

(1) Two photon-jet candidates with

$$\Delta R_J < 0.25,\ \log\theta_J < -0.8 \text{ and } N_{track} = 0$$

(2) The photon-jets are required to be isolated from nearby charged tracks within $\Delta R < 0.2$

(3) Two photon-jets are required to be boosted

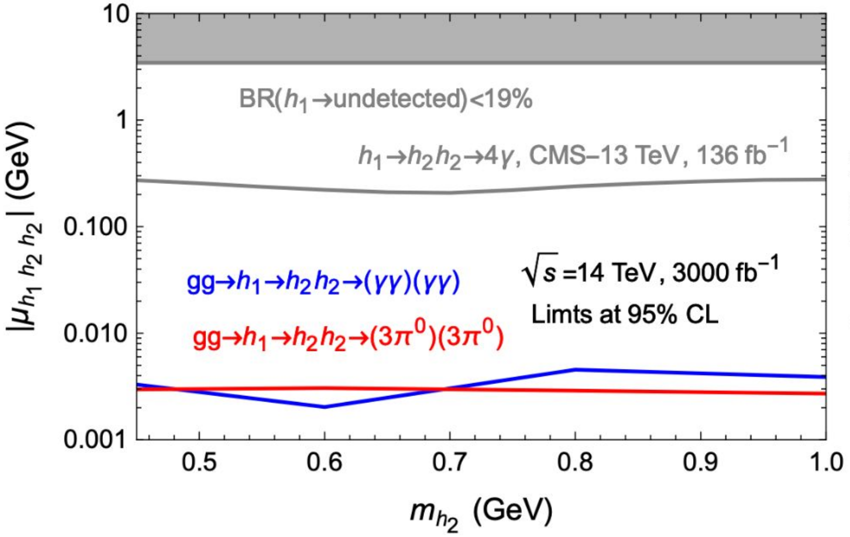
$$P_T(J_{1,2}) > 40 \text{ GeV and } |\eta| < 2.5$$

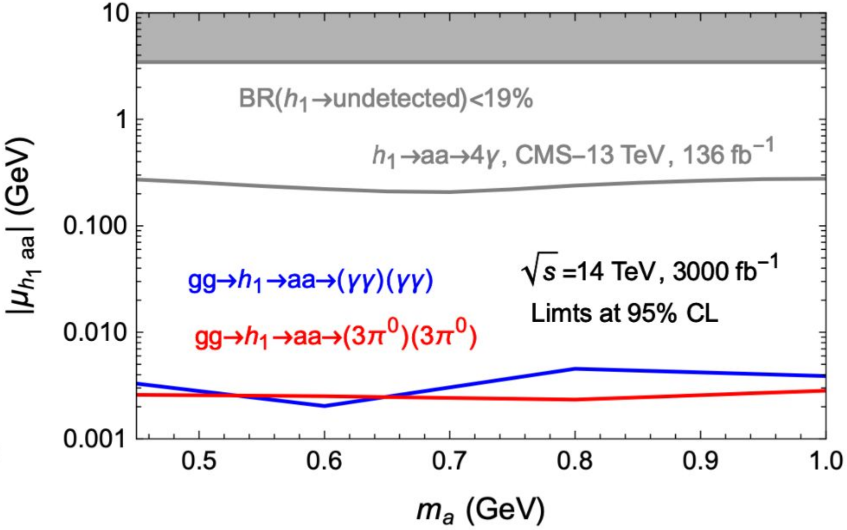
(4) The following selections are applied to further suppress the SM backgrounds

$$P_T(J_1) > 0.4 M_{J_1 J_2},\ P_T(J_2) > 0.3 M_{J_1 J_2}$$

$$120 < M_{J_1 J_2} < 130 \text{ GeV},$$

Physics Sensitivity based on CNN analysis





The branching ratio for each channel, i.e. h2/a → γγ, h2 → π0 π0 and a → π0 π0 π0 is assumed to be 1 in a model-independent way.

Contents

Conclusions

1. Photon-jets can be generated from a heavy resonance (EW scale or above) decaying to light resonance (sub-GeV scale), then to collimated photons.

2. The results show that both CNN and PFN are promising tools to separate the photon-jet signatures from SM backgrounds such as the single photon and $\pi 0$ from QCD jets.

3. The future bounds at HL-LHC can be much stronger than the existing constraint BR($h \rightarrow$ undetected) < 19%.

Thank you

for your attention