

Probing highly collimated photon-jets with deep learning

卢致廷 Chih-Ting Lu

06285@njnu.edu.cn



NNU · 南京师范大学
NANJING NORMAL UNIVERSITY

Collaborators :

Xiaocong Ai, Shih-Chieh Hsu and Ke Li

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**第十六届TeV工作组学术研讨会
暨邝宇平院士学术思想研讨会**

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1. Introduction
2. Photon-jet Identification with Deep Learning
3. Physics Sensitivity
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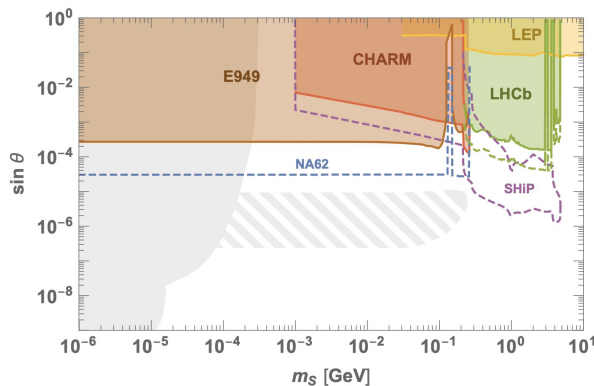
- 1. Introduction**
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Many extensions of the SM predict the existence of ALPs and/or dark Higgs in the sub-GeV scale.

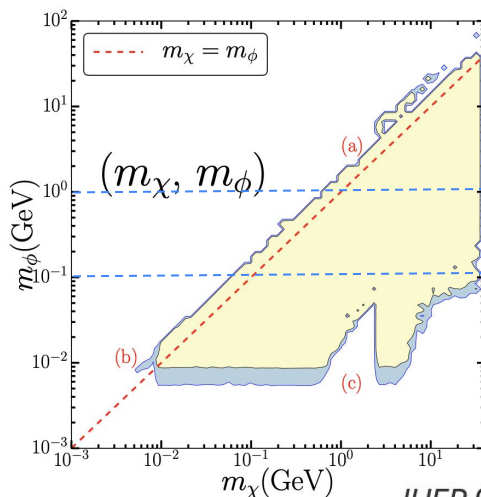
1. The mediator in sub-GeV DM models :

$$\mathcal{L} = \mathcal{L}_{\text{SM}} + \frac{1}{2}\bar{\chi}(i\not{\partial} - m_{\chi})\chi + \frac{1}{2}(\partial\Phi)^2 - \frac{c_s}{2}\Phi\bar{\chi}\chi - \frac{c_p}{2}\Phi\bar{\chi}i\gamma_5\chi - V(\Phi, H),$$

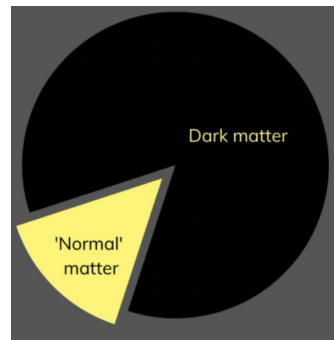
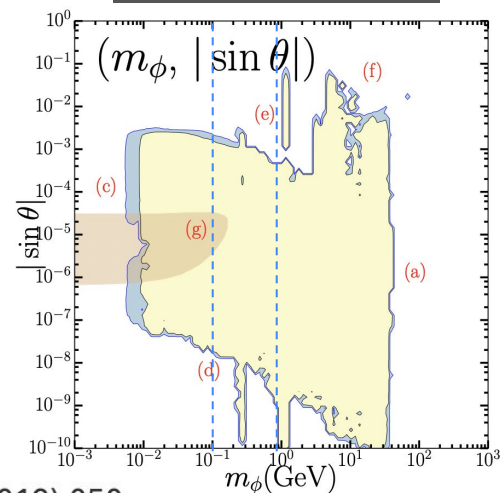
Z_2 symmetry



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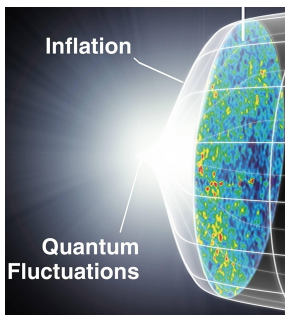
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Many extensions of the SM predict the existence of ALPs and/or dark Higgs in the sub-GeV scale.

2. Light inflaton models :

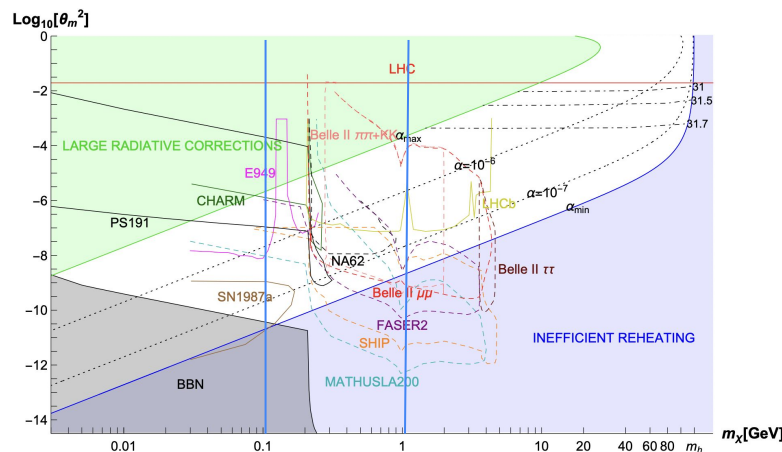
$$V(X, \Phi) = \frac{\beta}{4} X^4 - \frac{1}{2} \mu_X^2 X^2 - \mu_\Phi^2 \Phi^\dagger \Phi + \lambda \left(\Phi^\dagger \Phi + \frac{\alpha}{\lambda} X^2 \right)^2.$$



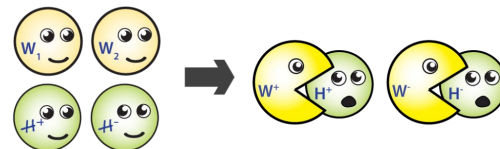
JHEP 05 (2010) 010

Phys.Rev.D 104 (2021) 7, 075020

etc ...

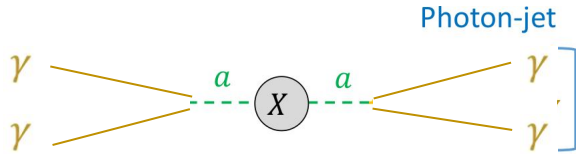


3. The dark Higgs mechanism to provide the dark photon mass



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

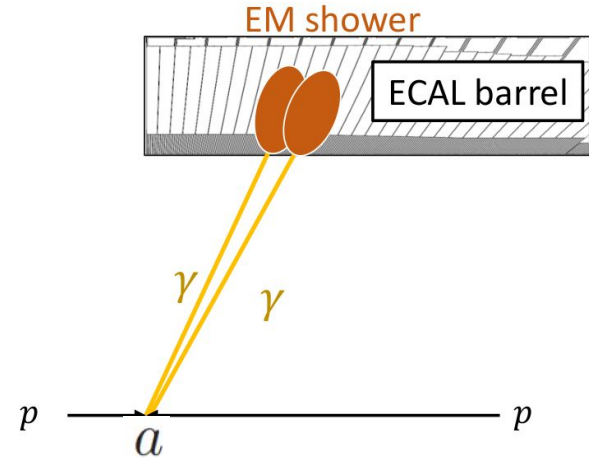


For $m_X = 125$ GeV and sub-GeV m_a ,
a photon-jet leads to one EM cluster

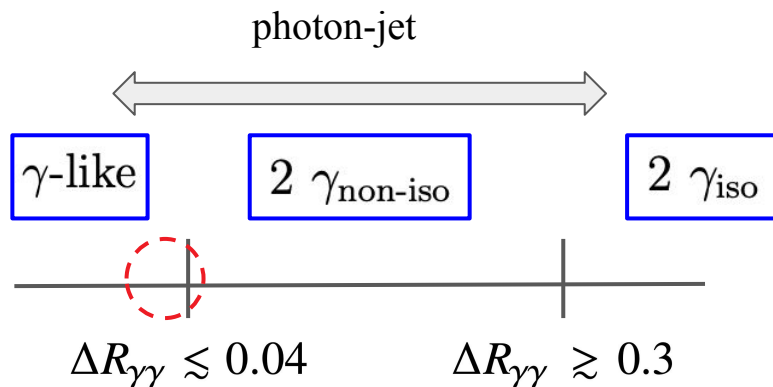
E.g. for $X \rightarrow aa \rightarrow 4\gamma$,

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

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



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

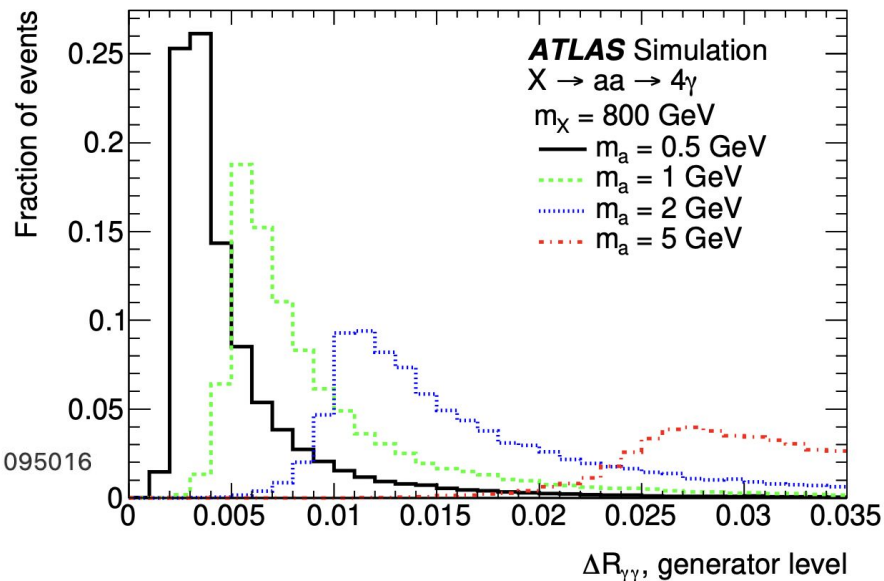


↑
ATLAS existing triggers
cannot distinguish them !

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

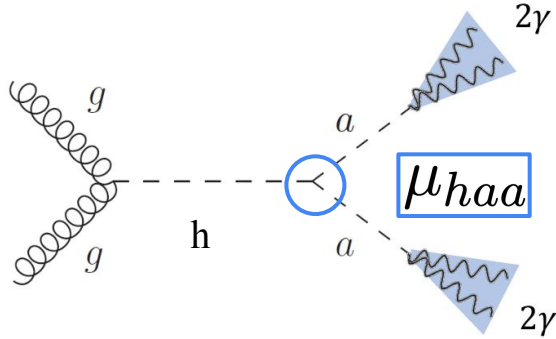
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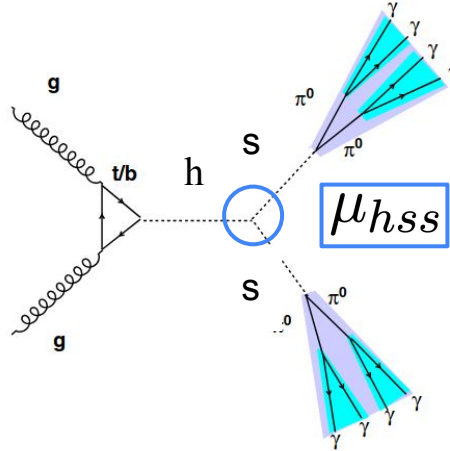


Topology of signal signatures

Photon-jet with 2 photons

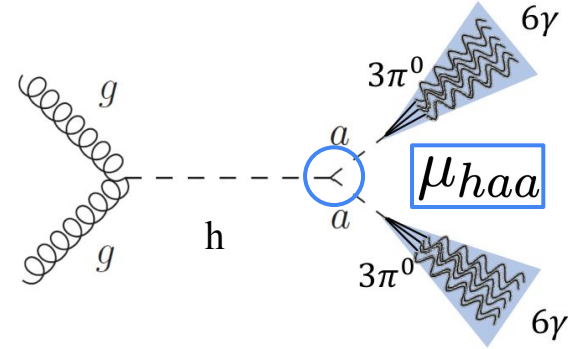


Photon-jet with 4 photons



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

Photon-jet with 6 photons



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

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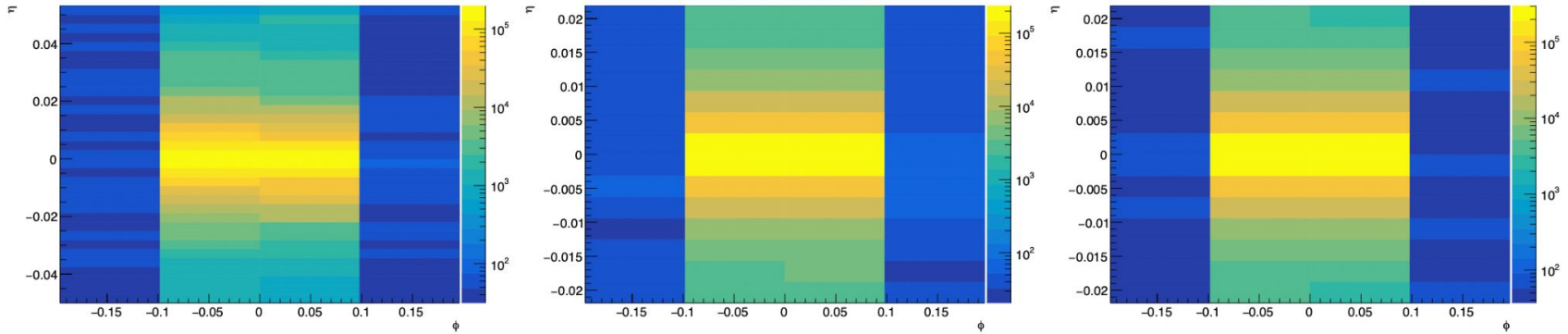
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Photon-jet Identification with Deep Learning

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 :

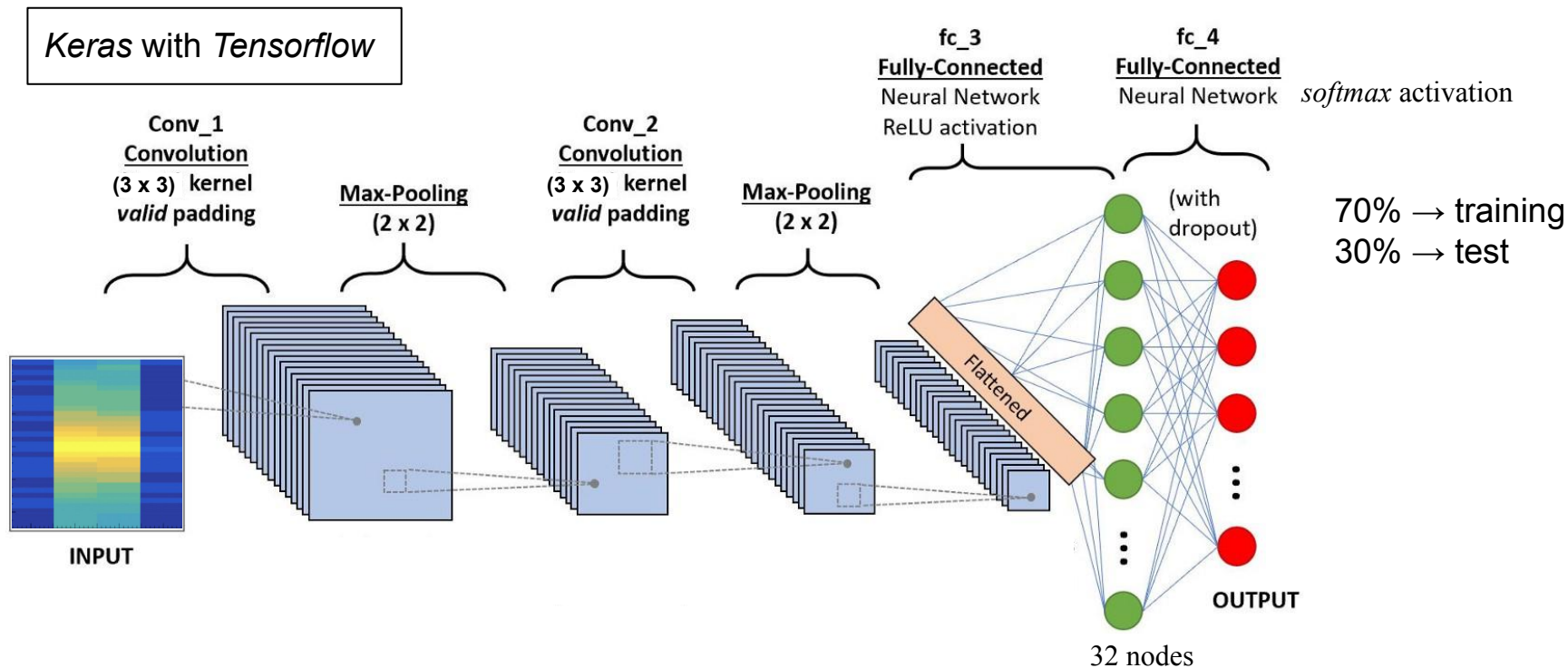


(a) $a \rightarrow \gamma\gamma$ ($m_a = 1$ GeV)

(b) γ

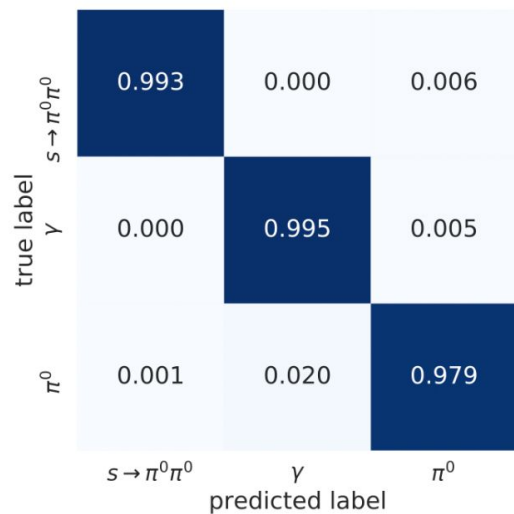
(c) π^0

Convolutional Neural Networks (CNN)

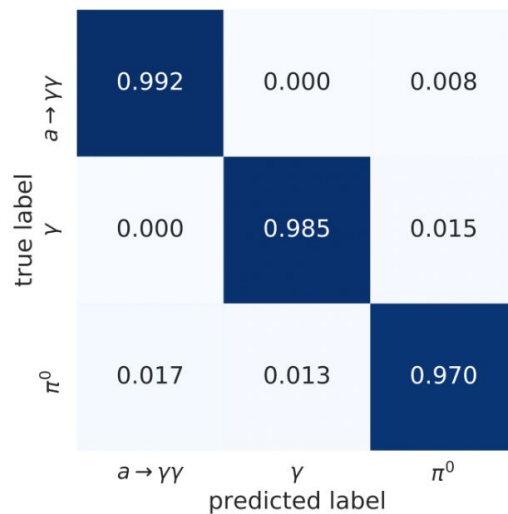


Convolutional Neural Networks (CNN)

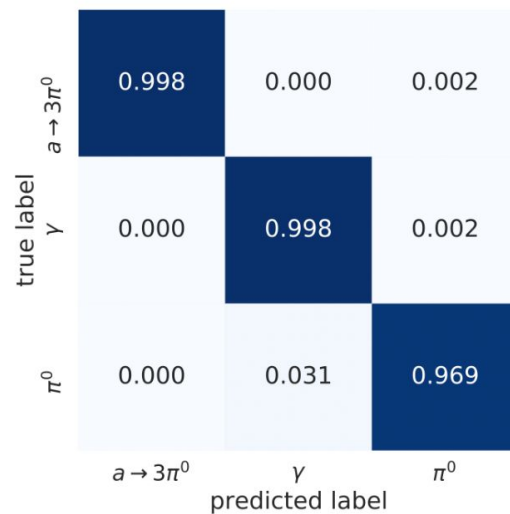
The normalized confusion matrix



(a) $s \rightarrow \pi^0 \pi^0$

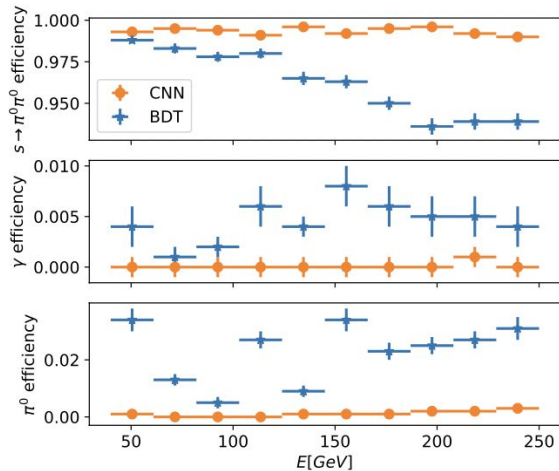


(b) $a \rightarrow \gamma \gamma$

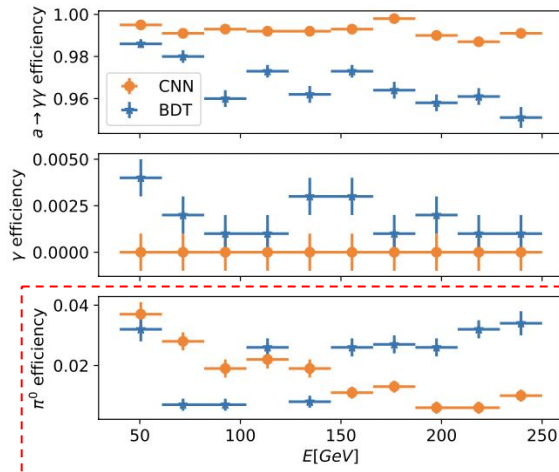


(c) $a \rightarrow \pi^0 \pi^0 \pi^0$

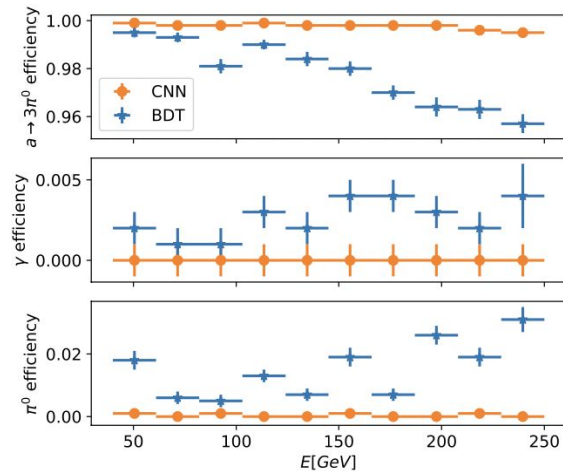
Comparison of performance between CNN and BDT



(a) $s \rightarrow \pi^0 \pi^0$



(b) $a \rightarrow \gamma \gamma$



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

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

Gradient Boosted Decision Trees (BDT)

$R_{\text{had}1}, R_{\text{had}}, R_{\eta}, \omega_{\eta2}, R_{\phi}, \omega_{s3}, \omega_{s\text{tot}}, f_{\text{side}}, \Delta E_s, E_{\text{ratio}}, f_1.$

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Simulation :

Feynrules : generate the UFO model files



MadGraph5 : generate the signal and background events



PYTHIA 8 : parton showering and hadronization



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

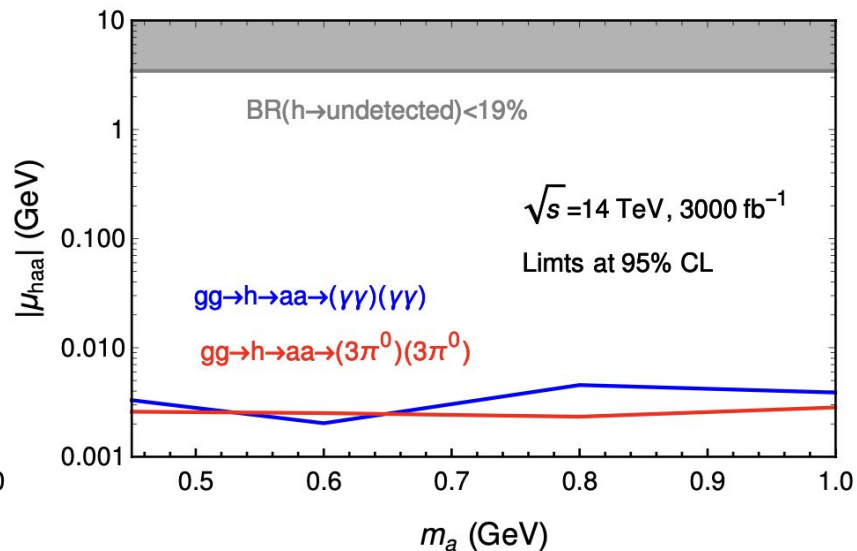
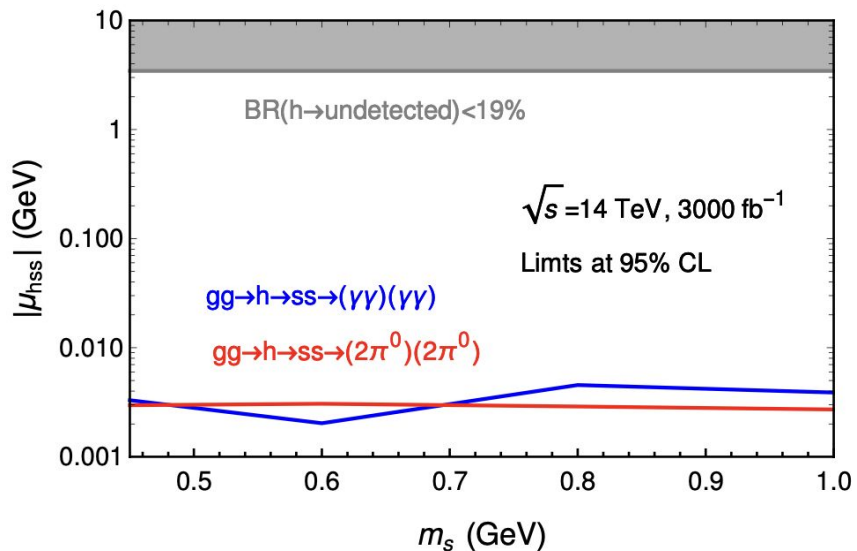
$$P_T(J_{1,2}) > 40 \text{ GeV and } |\eta| < 2.5$$

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

$$P_T(J_1) > 0.4M_{J_1J_2}, \quad P_T(J_2) > 0.3M_{J_1J_2}$$

$$120 < M_{J_1J_2} < 130 \text{ GeV,}$$

Physics Sensitivity



The branching ratio for each channel, i.e. $s/a \rightarrow \gamma\gamma$, $s \rightarrow \pi^0 \pi^0$ and $a \rightarrow \pi^0 \pi^0 \pi^0$ is assumed to be 1 in a model-independent way.

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Conclusions

1. The results show that the CNN is a promising tool to separate the photon-jet signatures from SM backgrounds such as the single photon and π^0 from QCD jets.
2. For photon-jet with energy above 150 GeV, CNN shows profound improvement with respect to BDT based on shower shape variables.
3. The future bounds at HL-LHC can be much stronger than the existing constraint $\text{BR}(h \rightarrow \text{undetected}) < 19\%$.

Thank you
for your attention