Search for new physics with one Higgs boson in the bbyy channel with the ATLAS detector

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Outline

Theoretical introduction and Higgs boson physics overview

The ATLAS experiment

Adaptation of a neural network algorithm for flavour tagging at HL-LHC

Search for additional scalar bosons in the $X \rightarrow SH \rightarrow bb\gamma\gamma$ channel

Theoretical introduction and Higgs boson physics overview

The Standard Model of particle physics

• The Standard Model (SM) describes and classifies the known elementary particles and their interactions. It's a quantum field theory based on the gauge invariance principle

Standard Model of Elementary Particles



- **Fermions** are the building blocks of matter They are divided into *quarks* (sensitive to the strong interaction) and *leptons*
- Gauge **bosons** support the interactions between them : the strong, weak and electromagnetic forces
- The **Higgs boson** is notably linked to the mass of the other particles

Higgs mechanism

- The Higgs mechanism explains the mass of the weak interaction bosons by the spontaneous breaking of the gauge symmetry
 - \rightarrow The Higgs field is a scalar field with non-zero vacuum expectation value
 - \rightarrow Other particles acquire their mass by interacting with this field
- The Higgs boson is an excitation of this field
 It's a scalar massive particle that was discovered in 2012







Higgs boson

The Higgs boson has been intensively studied since its discovery

- What we know :
 - Mass : m_{Higgs} = 125.25 \pm 0.17 GeV
 - Spin parity = 0^+ other possibilities excluded at 99% CL
 - Production modes, decay channels
 → Couplings to heavy particles
- \rightarrow Everything agree with the SM prediction for now

- What remains to discover :
 - Couplings to lighter fermions
 - Higgs self coupling

Decay channel	Branching ratio (%)
$H ightarrow bar{b}$	$58.2^{+0.70}_{-0.76}$
$H \rightarrow WW^*$	21.4 ± 0.32
H ightarrow gg	8.18 ± 0.42
$H o au^+ au^-$	6.27 ± 0.10
$H \rightarrow c \bar{c}$	$2.89^{+0.16}_{-0.06}$
$H \rightarrow ZZ^*$	2.62 ± 0.039
$H ightarrow \gamma \gamma$	0.227 ± 0.0048
$H \rightarrow Z\gamma$	0.153 ± 0.0089
$H ightarrow\mu^+\mu^-$	0.0218 ± 0.00037



Higgs boson self coupling

- Di-Higgs boson production (*HH*) allows a direct access to Higgs boson self coupling, a crucial parameter of the Higgs mechanism
 - → Difficult to probe since di-Higgs SM production rate is really low ($\sigma_{H} \approx 2000 \times \sigma_{HH}$)
 - Multiple decay channels must be combined to look for it Main ones : bbbb, bbττ and bbγγ





arXiv:2406.09971v2

- For now only upper limits have been set but we look for any deviations from SM predictions as it could indicate new physics
 - \rightarrow Di-Higgs is an major objective for HL-LHC

Beyond Standard Model (BSM) physics

- The SM does not describe all phenomena and has some shortcomings :
 - Does not provide a dark matter particle candidate
 - Does not explain neutrino oscillation
 - The 'Hierarchy problem' coming from Higgs boson divergent radiative corrections

 \rightarrow BSM physics consists in a variety of theoretical models that intend to fix (some of) the SM problems

- The Higgs sector is a promising place to look for BSM physics
 - Deviations from SM predictions could be observed in the Higgs properties
 - Some models (supersymmetry ...) extend the Higgs sector by introducing new particles which could be directly detected at the LHC → additional scalar sector



The ATLAS experiment

The Large Hadron Collider (LHC)

- The study of the Higgs boson requires high energy collisions
- This is done at the LHC at CERN
 - 27 km ring situated 100m underground
 - Proton-proton collisions up to 14 TeV
 - 4 detectors study the collisions : CMS, ALICE, LHCb and ATLAS
 - Different phases of operation :





Point 5 - CM

Point 1- ATLAS

Point 2 - ALICE

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Point 8 - LHC-b

The ATLAS Experiment

- ATLAS is a multipurpose detector that can study the Higgs boson, provide SM precision measurements and look for new physics
- 44m long, 25m tall, 7000 tons Four major components :
 - Inner Detector (ID) : trajectory reconstruction
 - Electromagnetic and hadronic calorimeters to measure particles energy

→ Photons and electrons reconstruction ^{magnet}
 → Jet reconstruction (collimated stream of hadrons coming from a guark production)

- Muon Spectrometer to detect muons
- Magnet system : bend charged particles trajectories and measure their impulsion



HL-LHC ATLAS and the Inner Tracker (ITk)

- The instantaneous luminosity will be increased during the HL-LHC era
 → More pile-up (i.e additional low energy interactions during beam crossings):
 from ~33 during Run-2 to up to 200 during HL-LHC
 - Busier environment (more tracks)
 - More radiation damage : HL-LHC fluence ~ 10 times larger than during Run 3
- The ATLAS detector will be upgraded and the ID will be replaced by ITk
 - 181 m² all-silicon detector with pixel and strip sensor types
 - Extended forward coverage from $|\eta| = 2.5$ to 4



Adaptation of a neural network algorithm for flavour tagging at HL-LHC

Flavour tagging

- Flavour (or b) tagging is the process of identifying the flavour of the quark at the origin of a jet
 It is essential for Higgs physics and analyses with b-jets in the final state
- Use *b*-hadrons properties to identify *b*-jets :
 - \circ Long lifetime \rightarrow secondary vertex (SV) displaced from the primary vertex (PV)
 - Tracks coming from the SV have large transverse d₀ and longitudinal z₀ impact parameters (IP) with respect to the PV





b-tagging algorithms in ATLAS

- ATLAS *b*-tagging algorithms :
 - 'Low' level algorithms (IP / SV based) use IP/SV information separately
 - 'High' level algorithms combine low level outputs to provide final *b*-tagging discriminant
 - More recently, GN1 is a graph neural network algorithm using tracks information



- **DIPS** is an impact parameter based algorithm
- Objective : train DIPS on the ITk upgrade configuration
 - Already done for older algorithms (IP3D, SV1, MV2)
 - Maintain (and possibly improve) *b*-tagging performance with harsher HL-LHC conditions

DIPS

• DIPS is a deep set neural network algorithm that takes tracks features as inputs They notably include the IP significances and the number of hits in certain layers of the detector



Track Input	Description			
S _d 0	d_0 / σ_{d0} : Lifetime signed transverse IP significance			
s_{z0}	$z_0 \sin \theta / \sigma_{z_0 \sin \theta}$: Lifetime signed longitudinal IP significance			
$\log p_T^{frac}$	log p_T^{track}/p_T^{jet} : Logarithm of fraction of the jet p_T carried by the track			
$\log \Delta R$	Logarithm of opening angle between the track and the jet axis			
nInnermostPixHits	Number of hits from the innermost pixel layer			
nNextToInnermostPixHits	Number of hits in the next-to-innermost pixel layer			
nInnermostPixShared	Number of shared hits from the innermost pixel layer			
nInnermostPixSplit	Number of split hits in the innermost pixel layer			
nPixHits	Number of pixel hits			
nPixShared	Number of shared pixel hits			
nPixSplit	Number of split pixel hits			
nStripHits	Number of strip hits			
nStripShared	Number of shared strip hits			

DIPS architecture

- A first network Φ handles each tracks inputs
- A second network F sums the different tracks and gives as an output the jet probability to be light / c / b flavoured

Jet selection

- Jet selection :
 - p_{τ} > 20 GeV and $|\eta|$ < 4
 - Some selections criteria needed to emulate future upgrade performance :
 - \rightarrow Reconstructed jets must be matched to a true jet to remove pile-up jets
 - \rightarrow Good PV reconstruction criteria (|truth PV reconstructed PV| < 0.1 mm)
- DIPS training is done with *tt* and *Z'* MC samples naturally rich in (*b*)-jets The training dataset is made of hybrid samples (70% *tt*, 30% *Z'*) designed to cover a large p_{τ} spectra



Flavour	tī	Z'	Total	
<i>b</i> -jets	4.1M	650k	4.8M	
c-jets	755k	700k	1.5M	
light jets	4.9M	1.1M	6M	

Flavour tagging performance

• Flavour tagging performance is evaluated with a ROC curve A discriminant is built from the algorithms output flavour probability *D* where *f_c* balances light and *c*-jet rejection

$$D_{\text{DIPS}} = \log \frac{p_b}{(1 - f_c)p_l + f_c p_c}$$



A threshold is determined on the discriminant distribution

→ All jets with a score above this threshold are tagged as *b*-jets, other ones are rejected

 \rightarrow A ROC curve shows the *c* and light jet rejection as a function of *b* efficiency parameterised by the threshold value

Upgrade DIPS performance



• DIPS performs much better than IP3D (older algorithm previously optimised for upgrade)



 DIPS performance degrades with η as expected because of the decreasing IP resolution Performance is a bit worse than Run-2 DIPS in the central region

DIPS preprocessing and training

The training dataset needs to have equal flavour repartition in p_τ and η bins
 → this is obtained with a procedure called resampling



picture from Kaggle

- Two methods are tested :
 - Count / undersampling : scale the number of jets to the minority class (c-jets)
 - **pdf** : target *b*-jet distribution and use a mix of under and oversampling
- 3M training jets with count, 15M with pdf Keep current Run-2 DIPS architecture

ι	Indersa	mpling	
Flavour	tī	Z'	Total
<i>b</i> -jets	755k	323k	1.07M
c-jets	755k	323k	1.07M
light jets	755k	323k	1.07M
			3.2M

Flavour	$t\bar{t}$	Z'	Total
<i>b</i> -jets	3.5M	1.5M	5M
c-jets	3.5M	1.5M	5M
light jets	3.5M	1.5M	5M
			15M

Tracks selection

The selection of the tracks used by the network can influence the performance
 A Tight and a Loose selection are defined and tested
 They differ by different selection criteria on p_T and transverse and longitudinal IP d₀ and z₀

	Tight tracks selection			
Requirements	$ \eta < 2.0$	$ 2.0 < \eta < 2.6$	$2.6 < \eta < 4.0$	
pixel + strip hits	≥ 9	≥ 8	≥ 7	
pixel hits	≥ 1	≥ 1	≥ 1	
pixel + strip holes	≤ 2	≤ 2	≤ 2	
p_T [MeV]	> 1000	> 1000	> 1000	
$ d_0 $ [mm]	≤ 1.0	≤ 1.0	≤ 1.0	
$ z_0 \sin \theta $ [mm]	≤ 1.5	≤ 1.5	≤ 1.5	
	Loose tracks selection			
		Loose tracks sele	ection	
Requirements	$ \eta < 2.0$	Loose tracks sele $2.0 < \eta < 2.6$	ection $2.6 < \eta < 4.0$	
Requirements pixel + strip hits	$\frac{ \eta < 2.0}{\geq 9}$	Loose tracks sele $2.0 < \eta < 2.6$ ≥ 8	$ \begin{array}{c} \text{ection} \\ 2.6 < \eta < 4.0 \\ \geq 7 \end{array} $	
Requirements pixel + strip hits pixel hits	$\frac{ \eta < 2.0}{\geq 9}$ ≥ 1	Loose tracks sele $2.0 < \eta < 2.6$ ≥ 8 ≥ 1	$ \begin{array}{c} \text{ection} \\ \hline 2.6 < \eta < 4.0 \\ \hline \geq 7 \\ \geq 1 \end{array} $	
Requirements pixel + strip hits pixel hits pixel + strip holes	$ \eta < 2.0$ ≥ 9 ≥ 1 ≤ 2	Loose tracks sele $2.0 < \eta < 2.6$ ≥ 8 ≥ 1 ≤ 2		
Requirements pixel + strip hits pixel hits pixel + strip holes p_T [MeV]	$ \eta < 2.0$ ≥ 9 ≥ 1 ≤ 2 > 900	Loose tracks sele $2.0 < \eta < 2.6$ ≥ 8 ≥ 1 ≤ 2 > 500	$ \begin{array}{r} \textbf{ection} \\ \hline 2.6 < \eta < 4.0 \\ \hline \geq 7 \\ \geq 1 \\ \leq 2 \\ \hline > 500 \\ \hline \end{array} $	
Requirementspixel + strip hitspixel hitspixel + strip holes p_T [MeV] $ d_0 $ [mm]	$ \eta < 2.0$ ≥ 9 ≥ 1 ≤ 2 > 900 ≤ 2.0	Loose tracks sele $2.0 < \eta < 2.6$ ≥ 8 ≥ 1 ≤ 2 > 500 ≤ 2.0		

• Max. 40 tracks per jet

Mean values : around 5 tracks / jet for *Tight*, around 7 tracks / jet for *Loose*

Results and trainings comparison

- The different tracks selection and resampling methods are compared :
 - Loose tracks selection better than Tight
 - pdf resampling method better than count
 - The *Loose* + pdf configuration provides the best performance



Global *b*-tagging performance in HL-LHC

• The selected DIPS model can then be used to perform an upgrade DL1d training The graph neural network based algorithm GN1 is also trained on the upgrade configuration Their performance is summed up in the <u>ATL-PHYS-PUB-2022-047</u> ATLAS public note

• 'All inclusive' graph neural network GN1 provides better results than the high level algorithm DL1d Future developments for flavour tagging at HL-LHC focus on the graph neural network approach



Search for two additional scalar particles in the $X \rightarrow S(\rightarrow b\bar{b}) H(\rightarrow \gamma \gamma)$ channel

Analysis presentation

- This analysis targets an asymmetric decay $X \rightarrow S(\rightarrow bb)H(\rightarrow \gamma \gamma)$ where X and S are new scalar bosons. and H is the SM Higgs boson Some theoretical models predict this phenomenology:
 - \rightarrow 2HDM with a complex or scalar singlet, NMSSM, TRSM ...
 - The search is model independent in order to be as general as possible
 - Only assumption made is signal generation with narrow width approximation





Dataset and event selection

- ATLAS Run-2 data (140 fb⁻¹ at 13 TeV) is used
- Use diphoton trigger which requires event to have $E_{\tau} > 35$ (25) GeV for the leading (subleading) photon
- The event selection is :
 - Two 'Tight' reconstructed and isolated photons which must also check $105 < m_{\gamma\gamma} < 160 \text{ GeV}$ and $p_{\tau}(\gamma_1) > 0.35 m_{\gamma\gamma} - p_{\tau}(\gamma_2) > 0.25 m_{\gamma\gamma}$ to target the $H \rightarrow \gamma\gamma$ decay
 - No lepton and between 2 and 5 central jets to reduce *ttH* background
 - One or two *b*-tagged jets at the 77% efficiency working point depending on the signal
 - The *b*-tagger used is DL1r

Different search regions

• A challenging situation arises when $m_s << m_x$: S is boosted and the *b*-jets coming from its decay are collimated and can be reconstructed as only one jet



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700 800

600

900 1000

m_x [GeV]

The $bb_{\gamma\gamma}$ channel

- Main backgrounds :
 - Non-resonant γγ+jets events
 - Resonant single Higgs : *ttH, ggH, ZH* and also *VBF H* in the 1 *b*-jet region
- Total number of selected events :

	1 b-tagged	2 b-tagged
HH	1.82 ± 0.27	1.68 ± 0.25
ttH	11.71 ± 1.1	8.12 ± 0.77
ZH	7.52 ± 0.17	3.64 ± 0.31
$\mathrm{ggF}H + bar{b}H$	57.5 ± 43	6.64 ± 5.3
Other single Higgs	17.4 ± 10	1.97 ± 0.7
Non resonant $\gamma\gamma$ +jets	16842 ± 122	1852 ± 40
Total	16936 ± 122	1874 ± 40



- Use the $m_{\gamma\gamma}$ distribution to define :
 - A signal region (SR) between 120 < m_w < 130 GeV
 - Control region sidebands (SB) on the side

PNN discriminant

- Parameterised neural networks (PNN) are used to discriminate signal from background in the SR
 → They use a vector of parameters θ in addition to the input event features vector x
- One PNN in each signal region
 - 2 *b*-tagged region : $\theta = (m_s, m_\chi)$, $x = (m_{bb}, m_{bbyy}^*)$,
 - 1 *b*-tagged region : $\theta = (m_{\chi}), x = (p_T^{b}, m_{b\gamma\gamma}^{*})$
- Training includes events from both the SR and the SB Training samples :
 - γγ+jets, ttH, ZH, ggH and corresponding region signals
 VBF H and HH also included in the 1 b-tagged region
- PNN output is a score between 0 and 1



Background modelling and MC - data agreement

- Background PNN distributions come from MC samples
- Data MC agreement in the PNN shape is checked in the SB The sideband distribution is used to normalize the γγ+jets process





Systematic uncertainties

- Main sources of experimental systematic uncertainties include particle identification (e.g flavour tagging) and p_{τ} and energy scale and resolution of the different objects
 - It changes the number of events in the SB and SR regions
 - It modifies the position and width of the peak in the m_{bb} and $m_{bb\gamma\gamma}$ distributions and eventually the shape of the PNN distribution

Experimental systematics are computed with dedicated variables that give the calibrated $\pm 1\sigma$ combined performance values

- \rightarrow Taken into account for signal, major single Higgs, HH, $\gamma\gamma$ +jets and Z(qq) $\gamma\gamma$ processes
- Theoretical systematic uncertainties :
 - SM parameters uncertainties (e.g α_s , QCD scale, branching ratio, PDF values) \rightarrow Might affect processes production cross-section
 - Parton shower modelisation by the MC generator

Experimental systematic uncertainties - Background values

 Systematic uncertainties variations to the PNN distribution are categorised through yield and shape changes
 Yield changes reflect the impact on selection and change with respect to nominal value

			Yield uncertainty (%)			
	Source	ttH	ZH	HH	ggH	
Event- based	Photon Trigger Pile-up reweighting	1.0 0.9	1.0 0.8	1.0 0.6	1.0 0.4	
Photon	Photon Energy Res. Photon Energy Scale Photon ID Photon Isolation	$0.4 \\ 0.2 \\ 1.6 \\ 1.6$	$0.4 \\ 0.2 \\ 1.6 \\ 1.6$	$0.3 \\ 0.1 \\ 1.4 \\ 1.5$	$0.4 \\ 0.1 \\ 1.6 \\ 1.6$	
Jet	Jet Energy Scale Jet Energy Res.	1.4 7.3	$\begin{array}{c} 0.9 \\ 4.6 \end{array}$	$\frac{0.6}{2.9}$	$1.8 \\ 7.5$	
Flavour- tagging	b-jet efficiency c-jet efficiency light-jet efficiency	2.1 0.4 0.8	$3.0 \\ 0.7 \\ 0.4$	$2.5 \\ 0.1 \\ 0.4$	$3.1 \\ 1.7 \\ 2.7$	

- This table shows the yield relative difference with respect to nominal value (in %) for the main background samples NB : γγ+jets normalization fixed by SB
- Major uncertainties are flavour tagging and jet energy resolution Relative difference remains below 10%

Experimental systematic uncertainties - Signal values

- For **signal**, the experimental systematic values depend on m_x and m_s
- Change is relatively constant for **photon systematics** because photons all come from the $H \rightarrow \gamma \gamma$ decay



Experimental systematic uncertainties - Signal values

• Relative difference is higher at low mass for flavour tagging



• Lower mass \rightarrow lower jet $p_{\tau} \rightarrow$ higher flavour tagging uncertainties

Experimental systematic uncertainties - Signal values

• Similarly, relative difference is higher at low mass for jet energy resolution



• Lower mass \rightarrow lower jet $p_{\tau} \rightarrow$ higher jet energy resolution uncertainties

Experimental systematic uncertainties - PNN shape variations

Example of shape changes in the PNN distribution for one jet energy resolution uncertainty in the γγ+jets and signal samples
 The variation in the last signal like bin doesn't exceed 10%


Analysis results

• Results are obtained with a binned likelihood fit on the PNN shape distribution



• Systematic uncertainties are taken into account in the fit as nuisance parameters

Analysis results - Experimental uncertainties impact

• Systematic uncertainties impact can be assessed by comparing **blinded** limits obtained when they are taken into account to when they are not



 Experimental uncertainties impact is really low at high mass (below 1%) but can reach 20% at low mass due to large signal uncertainties

Analysis results - Signal significance

- Discovery statistical tests are performed for every considered mass point The largest excess with respect to the background only hypothesis is observed for (m_x, m_s) = (575, 200) GeV Local (global) statistical significance is 3.5σ (2.0σ)
- No excess is noticed for $(m_{\chi}, m_{s}) = (650, 90)$ GeV where CMS observed a local (global) 3.8 σ (2.8 σ) deviation



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Analysis results - Limits

• Limits are set on the production cross section times *bbyy* branching ratio in the mass space



• Limits range from 0.09 fb at high mass to 39 fb at low mass Best sensitivity achieved in the high mass region thanks to a better signal efficiency

Analysis perspective

- The analysis has been submitted to JHEP Preprint is already available <u>arXiv:2404.12915</u>
- New perspectives will be offered with the upcoming Run 3 data
 - Already more statistics than Run 2, which will allow to shed more light on the observed excesses
 - The analysis techniques developed for the bbγγ final state can be useful for the HH research in the same channel

Conclusion

- Training of a *b*-tagging neural network algorithm with the HL-LHC configuration
 - Run 3 and HL-LHC will greatly increase the available data statistics
 → Crucial to study and optimize future detector performance
 - DIPS obtains better performance compared to previous upgrade studies
 - Future developments will focus on the graph neural network approach

- Research of two additional scalar bosons in the $X \rightarrow SH \rightarrow bb\gamma\gamma$ channel
 - First analysis to probe an uncharted phase space for low m_s and m_x values
 - Systematic uncertainties impact is assessed over the whole mass space
 - Largest deviation of 3.5 σ (2.0 global) at (m_{χ} , m_{s}) = (575, 200) GeV \rightarrow No deviation observed for CMS 3.8 σ local excess at (m_{χ} , m_{s}) = (650, 90) GeV
 - Limits from 0.09 to 39 fb are set on the production cross section in the bbγγ channel

Backup

Di-Higgs production

• Interfering 'triangle' and 'box' diagrams for ggF HH production - $\sigma_{ggF}(HH)$ = 31 fb Phys. Rev. D 106, 052001 (2022)





 κ_t

• VBF HH production also allows to probe κ_v and κ_{2v} - σ_{VBF} (HH) = 1.73 fb



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Luminosity and pile-up at (HL)-LHC

• Mean pile-up throughout LHC runs - latest plot available <u>here</u>

• Integrated luminosity per year



ITk tracking dependence in $|\eta|$

- ITk material distribution expressed in radiation lengths (X_0) in function of pseudorapidity $|\eta|$
- 3.5 Radiation Lengths $[X_0]$ Moderator **ATLAS** Preliminary PP1 and enclosure Dry Nitrogen Strip services and cooling Simulation Strip supports Strip modules ITk Layout : 23-00-03 Pixel services and cooling Pixel supports Pixel modules 🔆 Beam pipe and IPT 1.5 0.5 0.5 1.5 0 2.5 3 3.5 4.5 η ATL-PHYS-PUB-2021-024

 Transverse IP resolution as a function of |η|



DIPS tracks inputs

• Distribution of the number of tracks per jet in the *Tight* (left) and *Loose* (right) tracks selection





DIPS tracks inputs

• Tracks origin in *tt* samples for *Tight* (left) and *Loose* (right) tracks selection (flavour inclusive)



DIPS upgrade training metrics

• Training loss evaluated on the training and validation sets

Count training w/ loose tracks selection







Upgrade DIPS additional performance plots

• Performance evaluation on Z' samples (probes high p_{τ} jets)





Upgrade DIPS additional performance plots

• Performance p_{τ} dependence





Upgrade DIPS additional performance plots

• Fraction scan plots shows the balance between light and *c*-jet rejection with curves parameterized by f_c



Graph neural network *b*-tagging algorithms

• GN1 inputs for upgrade training

Jet Input	Description
p_{T}	Jet transverse momentum
η	Signed jet pseudorapidity
Track Input	Description
q/p	Track charge divided by momentum (measure of curvature)
$d\eta$	Pseudorapidity of the track, relative to the jet η
$\mathrm{d}\phi$	Azimuthal angle of the track, relative to the jet ϕ
d_0	Closest distance from the track to the PV in the longitudinal plane
$z_0 \sin \theta$	Closest distance from the track to the PV in the transverse plane
$\sigma(q/p)$	Uncertainty on q/p
$\sigma(\theta)$	Uncertainty on track polar angle θ
$\sigma(\phi)$	Uncertainty on track azimuthal angle ϕ
$s(d_0)$	Lifetime signed transverse IP significance
$s(z_0\sin\theta)$	Lifetime signed longitudinal IP significance
nPixHits	Number of pixel hits
nStripHits	Number of strip hits
nInnermostPixHits	Number of hits from the innermost pixel layer
nNextToInnermostPixHits	Number of hits from the next-to-innermost pixel layer
nInnermostPixShared	Number of shared hits from the innermost pixel layer
nInnermostPixSplit	Number of split hits from the innermost pixel layer
nPixShared	Number of shared pixel hits
nPixSplit	Number of split pixel hits
nStripShared	Number of shared strip hits
nPixHoles	Number of pixel holes
nStripHoles	Number of strip holes

 Increase in performance allowed by GNNs for Run 2 and Run 3 <u>FTAG-2023-01</u>



Signal selection efficiency

• Signal selection efficiency in the 1 *b*-tagged (left) and 2 *b*-tagged (right) jet regions



Expected number of events

• Obtained from a background only fit in the 2 *b*-tagged (left) and 1 *b*-tagged (right) jet regions

		2 <i>b</i> -tagged region		1 <i>b</i> -tagged region		
Background	Sideband	Signal region	Signal-like bin	Sideband	Signal region	Signal-like bin
Non-res. $\gamma\gamma$	1480 ± 37	372 ± 16	1.64 ± 0.37	13450 ± 110	3392 ± 53	2.45 ± 0.43
Single Higgs	0.46 ± 0.11	19.9 ± 5.3	0.04 ± 0.01	2.3 ± 1.1	92 ± 44	0.21 ± 0.10
ggF+ $b\bar{b}H$	0.14 ± 0.11	6.5 ± 5.2	0.01 ± 0.01	1.5 ± 1.1	56 ± 43	0.11 ± 0.09
tīH	0.21 ± 0.01	7.91 ± 0.77	0.01 ± 0.01	0.31 ± 0.01	11.4 ± 1.1	0.03 ± 0.01
ZH	0.08 ± 0.01	3.56 ± 0.30	0.02 ± 0.01	0.17 ± 0.01	7.35 ± 0.60	0.02 ± 0.01
Other	0.03 ± 0.01	1.94 ± 0.70	< 0.005	0.40 ± 0.23	17 ± 10	0.05 ± 0.03
Double Higgs	0.03 ± 0.01	1.65 ± 0.25	< 0.005	0.03 ± 0.01	1.79 ± 0.27	0.01 ± 0.01
Total	1480 ± 37	394 ± 16	1.67 ± 0.37	13450 ± 110	3486 ± 48	2.67 ± 0.45
Signal (m_X, m_S)						
(250, 100) GeV	0.38 ± 0.04	8.3 ± 1.2	1.43 ± 0.21			
(1000, 70) GeV				0.97 ± 0.10	33.3 ± 5.8	23.9 ± 4.2
Data	1479	395	0	13450	3491	4

PNN inputs

• 2 *b*-tagged region PNN inputs distribution



PNN inputs

• 1 *b*-tagged region PNN inputs distribution



 m_{yy} fit strategy

• Sensitivity comparison (expected limits) between the different analysis strategy



Data - MC agreement

• 2 *b*-tagged region PNN inputs sidebands distribution





m_{bb}

Data - MC agreement

1 *b*-tagged region PNN inputs sidebands distribution \bullet



 $p_{\rm T}^{\ b}$

450

500

 p_{τ}^{b} [GeV]

Systematic uncertainties

• Summary table of experimental and theoretical systematic uncertainties taken into account in the analysis

		Signal	HH ggF	HH VBF	ttH & ZH	Other Single Higgs	Continuum $\gamma\gamma$ +jets	
Theory	Normalisation	$BR(H \to \gamma \gamma)$	$BR(H \to \gamma \gamma)$ $BR(H \to b\bar{b})$ $PDF + \alpha_S$ $Scales + m_t$	$BR(H \to \gamma \gamma)$ $BR(H \to b\bar{b})$ $PDF+\alpha_S$ $Scales$	$BR(H \to \gamma \gamma)$	$BR(H \to \gamma \gamma)$ $PDF+\alpha_S$ $Scales$	γγ transfer factor	
	Shape+Norm.	Scales, PDF+ α_S Parton shower Interpolation	Parton Shower		Scales, PDF+ α_S Parton Shower		Scales, PDF+ α_S Modelling	
Exp.	Shape+Norm.	Pile-up modelling Diphoton trigger efficiency Photon identification and isolation efficiency Photon energy scale and resolution Jet energy scale and resolution Jet vertex tagger efficiency Flavour tagging efficiency						

Theoretical uncertainties impact

• Theoretical systematic uncertainties impact on the limit They are dominated by the γγ+jets modelling uncertainty



• The impact on the limit can be as large as 20% in the 2 *b*-tagged region and 40% in the 1 *b*-tagged region

Jet $p_{_{T}}$

• Signal leading jet p_{T} distribution for two different mass points



Ranking plots

• Example of ranking plots showing the impact on the fit of the 15 more important NP in two points



Δμ 0.0 -0.20.4 0.2 -0.4yy_Modelling yy_theory_TF signal PartonShower ggH theory JET_JER_EffectiveNP_2 signal PDFalpha JET_JER_EffectiveNP_4 JET_JER_EffectiveNP_3 yy_norm JET_JER_EffectiveNP_1 BR_Hyy staterror_SR[7] yy_QCD FT_EFF_Eigen_C_0 signal_pdf_set

$(m_{\chi}, m_{S}) = (230, 15) \text{ GeV} - 1 b$ -tagged region

Interpolation

• Required granularity is assessed with signal injection tests to be sure not to miss any signal







PNN and interpolation

• Example of PNN distribution in the 1 *b*-tagged region $(m_{\chi}, m_{s}) = (1000, 70) \text{ GeV}$



• PNNs are sensible to signals with masses close to their parameters



Post-fit PNN distributions

SR post-fit PNN distribution for (m_x, m_s) = (250, 100) GeV (left - 2 b-tagged region) and (m_x, m_s) = (1000, 70) GeV (right - 1 b-tagged region)
 NB : signal distributions in blue normalised to σ = 1 fb



Expected limits





10-1

CMS S/YH \rightarrow bbyy analysis

- JHEP 05 (2024) 316
- Mass range probed : 260 < m_{χ} < 1000 GeV, 90 < m_{S} / m_{γ} < 800 GeV

→ 6 different BDT in different (m_{χ}, m_{s}) regions to discriminate signal from non resonant background → For m_{χ} < 550 GeV DNN to discriminate signal from Resonant background





• Results obtained with a max. likelihood fit of the $m_{\gamma\gamma}$ and m_{jj} distributions

Limits from 0.04 to 0.90 fb

CMS results - 3.80 local excess

- Logal (global) 3.8 σ (below 2.8 σ) excess at $(m_{\chi}, m_{S}) = (650, 90) \text{ GeV}$
- We perform a signal injection at the same point with a signal cross section of 0.35 fb (CMS best fit value)

This signal injection gives an expected local excess of 2.7 standard deviation whereas we do not see any excess with respect to the background only hypothesis ($p_0 > 0.5$)



Other $X \rightarrow SH$ results in different channels

• CMS combination of *bbγγ*, *bb*ττ and *4b* channels <u>arXiv:2403.16926</u>





Non resonant HH analysis

• Resonant + non resonant $HH \rightarrow bb\gamma\gamma$ paper <u>Phys. Rev. D 106 (2022) 052001</u> Legacy non resonant $HH \rightarrow bb\gamma\gamma$ paper <u>JHEP 01 (2024) 066</u>

