Using Machine Learning in the search for dark photons in the $H \rightarrow Z + \gamma_d$ with the ATLAS detector at the LHC.

Karabo Tau[1], **Rachid Mazini**[1] **and Mukesh Kumar**[1]

[1]School of Physics, University of the Witwatersrand, Johannesburg 2050, South Africa

E-mail: `2341256@students.wits.ac.za`

Abstract. The search for new physics is one of the key goals of the ATLAS Collaboration. With the discovery of the Higgs boson in 2012, the Standard Model (SM) gained an essential ingredient towards the understanding of fundamental particles and their interactions — but it cannot yet be considered complete. The nature of dark matter (DM), which constitutes about 27% of the universe, remains a major open question. Dark matter may belong to a complex “dark sector” of particles beyond the SM, with its own internal symmetries and interactions. Among these hypothetical particles, the "dark photon" (γ_d) is a predicted mediator for interactions within this sector. If dark photons couple to SM particles, they could be produced in high-energy proton-proton collisions at the LHC and detected by the ATLAS experiment. This study investigates the production of γ_d via Higgs boson decay $H \rightarrow Z + \gamma_d$, where the Z boson decays into two leptons of the same flavor and opposite sign (e^+e^- or $\mu^+\mu^-$), and the undetected γ_d results in missing transverse energy (E_T^{miss}). The resulting final state, $e^+e^-/\mu^+\mu^- + E_T^{\text{miss}}$, provides a distinct signature for the presence of γ_d. However, the SM presents several physics processes with similar final states that are produced with a higher probability in pp collisions. To distinguish the γ_d signal from these backgrounds, Machine Learning (ML) algorithms are employed. Algorithms such as Boosted Decision Trees (BDT), Deep Neural Networks (DNN), and Graph Neural Networks (GNN) are trained on ATLAS Monte Carlo simulation data to identify the most effective method for signal-background discrimination. The selected model is then applied to ATLAS data to enhance sensitivity in the search for dark photons.

1 Introduction

The nature of dark matter (DM) remains an open major question. Although there is strong astrophysical evidence suggesting the existence of dark matter with a density about five times higher than ordinary baryonic matter, its fundamental nature is unknown [1]. DM could be part of a dark sector and potentially interacting with the SM sector. The dark sector is assumed to exist as a world parallel to our own [**?**]. It is a hypothetical collection of fields and particles predicted as possible SM extensions with no direct interactions, which couples extremely weakly to SM through mediating particles such as dark photons ("portal" interactions). Dark photons are predicted in hidden-sector models with an unbroken dark U(1) gauge symmetry, which either kinetically mixes with the SM photon or couple to the Higgs sector via mediators and could be produced through portals: vector portal (spin 1), Higgs portal (scalar), neutrino portal (spin 1/2) and axion portal (pseudo-scalar). From these possible portals, the vector portal is the one where the interaction results from the kinetic mixing between one dark and one visible Abelian gauge boson. The visible photon is taken to be the boson of the U (1) gauge group of electromagnetism or, above the electroweak symmetry-breaking scale, of the hyper charge, while the dark photon is identified as the boson of an extra U(1) symmetry [2][**?**]. Due to its kinetic mixing with the visible photon, the dark photon can still be detected even though it is dark. This kinetic mixing provides the portal linking the dark and visible sectors. It is this portal that makes it possible to detect the dark photon in the experiments. Looking beyond particles physics and towards cosmology, many dark photons models were introduced to improve astroparticle and cosmology models. It could also help with the Yukawa hierarchy and the small-scale structure formation problems in cosmology.

1.1 $H \to Z + \gamma_d$ Theoretical Framework

We use a minimal model to generate at 1-loop where $H \to \gamma\gamma_d$, $Z\gamma_d$ decays as shown in Figure 4. The model introduces two scalar messengers: $SU(2)_L$ doublet S_L and $SU(2)_L$ scalar singlet S_R. The scalar messengers mix with the Higgs field via a generic interaction Lagrangian:

$$\mathcal{L} \sim \mu\,(H^\dagger S_L S_R + \text{h.c.})$$

which is manifestly $SU(2)_L$ invariant, and μ is a mass parameter.

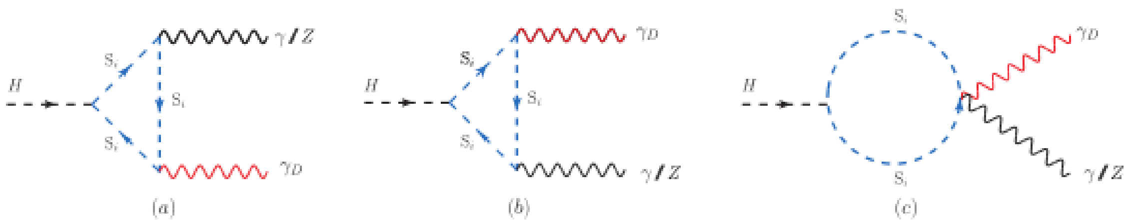

Figure 1: Feynman diagrams of the $H \to \gamma\gamma_d$, $Z\gamma_d$ decays.

The Branching Ratios of $H \to \gamma\gamma_d$, $Z\gamma_d$, $\gamma_d\gamma_d$, $\gamma\gamma$ have the following model-independent parameterization:

$$\begin{aligned}
\mathrm{BR}_{\gamma\gamma_D} &= \frac{\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}\, r_{\gamma\gamma_D}}{1 + r_{\gamma_D\gamma_D}\,\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}}, \\
\mathrm{BR}_{Z\gamma_D} &= \frac{\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}\, r_{Z\gamma_D}}{1 + r_{\gamma_D\gamma_D}\,\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}}, \\
\mathrm{BR}_{\gamma_D\gamma_D} &= \frac{\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}\, r_{\gamma_D\gamma_D}}{1 + r_{\gamma_D\gamma_D}\,\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}}, \\
\mathrm{BR}_{\gamma\gamma} &= \frac{\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}\,\left(1 + \chi\sqrt{r_{\gamma\gamma}}\right)^2}{1 + r_{\gamma_D\gamma_D}\,\mathrm{BR}^{\mathrm{SM}}_{\gamma\gamma}}.
\end{aligned} \tag{1}$$

The r_i parameters are given by:

$$\begin{aligned}
r_{\gamma\gamma_D} &= 2X^2\left(\frac{\alpha_D}{\alpha}\right), \\
r_{Z\gamma_D} &= 2X^2 R_Z^2\left(\frac{\alpha_D}{\alpha}\right), \\
r_{\gamma_D\gamma_D} &= X^2\left(\frac{\alpha_D}{\alpha}\right)^2, \\
r_{\gamma\gamma} &= X^2,
\end{aligned} \tag{2}$$

$$X \equiv \frac{\xi^2}{3F(1-\xi^2)}, \quad \xi \equiv \frac{\Delta}{\tilde{m}^2} \tag{3}$$

where $F \sim 6.5$ comes from the SM $H \to \gamma\gamma$ form factor, and Δ depends on the mass difference of the two scalars.

1.2 *The ATLAS Detector*

The ATLAS detector at the LHC is a multi-purpose particle detector. With a forward–backward symmetric with respect to the interaction point. It consists of an inner tracking detector (ID) surrounded by thin superconducting solenoid, electromagnetic, and hadron calorimeters, as well as a muon spectrometer incorporating three large superconducting air-core toroidal magnets [**?**]. The inner detector system (ID) is s surrounded by a 2 T superconducting solenoidal field. The ID tracks charged particles, allowing for particle identification and vertex measurements. The system provides charged-particle tracking in the range of $|\eta| < 2.5$. The electromagnetic calorimeter (EM-CAL) surrounds the ID and absorbs energy from particles that interact electromagnetically as they move through the detector. The EMCAL covers $|\eta| < 3.2$. The Hadronic calorimeter (HCAL) surrounds the EM calorimeter and is made up of steel plates and plastic scintillator plates which absorb energy from hadrons. These HCAL constituents provide hadronic coverage of $|\eta| < 1.7$, and LAr technology is also used for the HCAL end-cap region. The entire HCAL covers a pseudorapidity range of $|\eta| < 4.9$ [2]. The muon spectrometer defines the overall dimensions of the ATLAS detector [2]. It consists of three large superconducting toroid systems of high-precision tracking chambers that provide exceptional muon momentum measurement.

1.3 *Search for $H \to Z + \gamma_d$*

The signal process of a Higgs boson decaying into a Z boson and an invisible dark photon was generated in the ZH production mode. The signal events are the gluon-gluon fusion and the vector-boson fusion processes. The signal region is defined by the $e^+e^-/\mu^+\mu^- + E_T^{\text{miss}}$ final state. The two same-flavour, oppositely charged leptons come from a Z boson decay, the photon comes from the Higgs boson decay, and the E_T^{miss} comes from the undetected dark photon. The analysis is affected by a large variety of background processes. The irreducible backgrounds come from (VVγ) final states where V is any of the W/Z bosons with both bosons decaying leptonically and associated production of a Z and Higgs boson decaying to neutrinos and bosons. Reducible backgrounds come from E_T^{miss}, most likely due to undetected particles or hadronic jets not fully contained in the detector acceptance or from particle misidentification. The top-quark pair production with both tops decaying leptonically and the single top production with leptons and b-jets. This is ongoing work; Table 2 lists the event kinematic selections that have been applied to both the signals events (ggHZγ_d and VBFHZγ_d) and background events ($llvv$, $t\bar{t}$ and $Z + jets$),so far.

Two leptons (e^+e^- / $\mu^+\mu$)
Leading $p_T > 27$ GeV and sub-leading $p_T > 15$ GeV
Electron η cut: $|\eta|$ < 2.47, exclude 1.37 < $|\eta|$ < 1.52
Muon η cut: $|\eta|$ < 2.7
Dilepton invariant mass: 65 GeV $< m_{\ell\ell} < 110$ GeV
Missing transverse energy MET > 15 GeV
$N_{\text{jet}} \leq 2$, with $p_T^{\text{jet}} > 30$ GeV, $|\eta| < 4.5$

Table 1: Kinematic selection criteria for the $\ell^+\ell^- + E_T^{\text{miss}}$ signal region.

1.4 *Machine Learning*

Machine learning (ML) is a process by which a computer is able to complete a task without explicit instruction, but through inference and patterns. This is done by first training the algorithm using sample (training) data that is a representation of the data that the algorithm will be used to analyze[3]. ML algorithms can be divided into two types: Supervised algorithms learn how to match inputs to outputs based on example input-output pairs in the training data. The algorithm requires a target class, referred to as labels, for the collection of features. Supervised algorithms can be further sub-divided into classification and regression tasks. Classification tasks are those that wish to predict whether the data falls into some category or another. Regression tasks aim to model the relationship between a dependent(target) and independent (predictor) variables with one or more independent variables. Unsupervised algorithms are those that do not have labels, they find patterns inherent in the data structure. Tasks can be split into: clustering, association and dimensionality reduction. Clustering is a data mining technique that groups unlabeled data based on some similarity measure. Association looks for relationships between variables in a given dataset. Dimensionality reduction looks to represent data in a lower dimensional form, whilst preserving the data integrity[3]. This aids in processes like noise reduction, data visualisation, and clustering.

1.5 Signal Region Optimization

To improve the sensitivity of the search for γ_d signal, the boosted decision tree (BDT) algorithm was implemented using the XGBoost classifier [3]. For training and testing the model, all events entering the SR are used. All signal events are assigned to the positive label (y = 1) and all background events are assigned to the negative label (y = 0) in the training data. Training was done on 75% and testing was done on 25%. To train the model the feature set consisting of the input variables shown in Table 2 was used.

p_T lepton, ΔR (lepton)
MET , MET significance
$\Delta\phi$ (MET,Z)
$\Delta\phi$ (MET, γ_d)
p_z (longitudinal γ_d)
m_T (ll, MET) discriminant variable for global fit

Table 2: Input variables for the BDT

2 Results

This section will cover the preliminary results that were achieved from implementing the kinematic selection criteria shown in Table 2. The results are a comparison of MET for the signal distributions (ggHZγ_d and VBFHZγ_d) and background distributions ($llvv$ and $t\bar{t}$). As well as the preliminary results of the BDT study.

2.1 Signal distributions

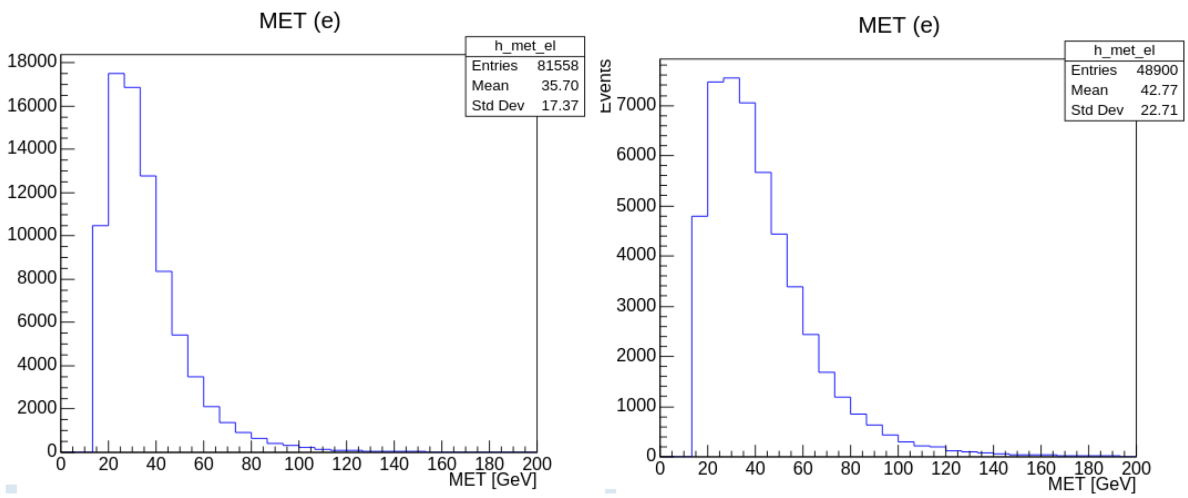

Figure 2: (*left*) Missing Transverse Energy for the signal: ggHZγ_d. (*right*) Missing Transverse Energy for signal: VBFHZγ_d.

2.2 Background distributions

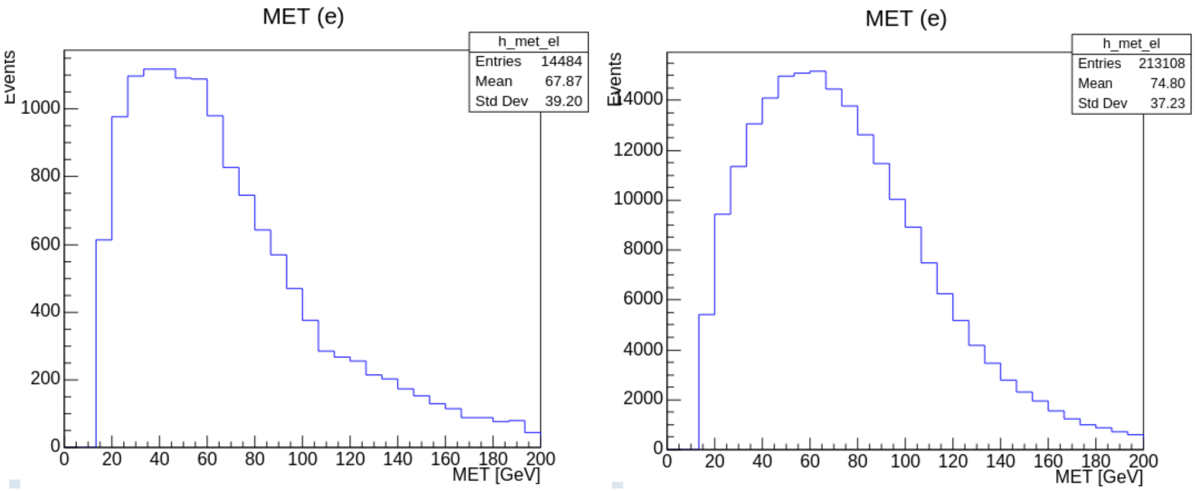

Figure 3: (*left*) MET for the background: $llvv$. (*right*) MET for the background: $t\bar{t}$

2.3 Preliminary BDT study

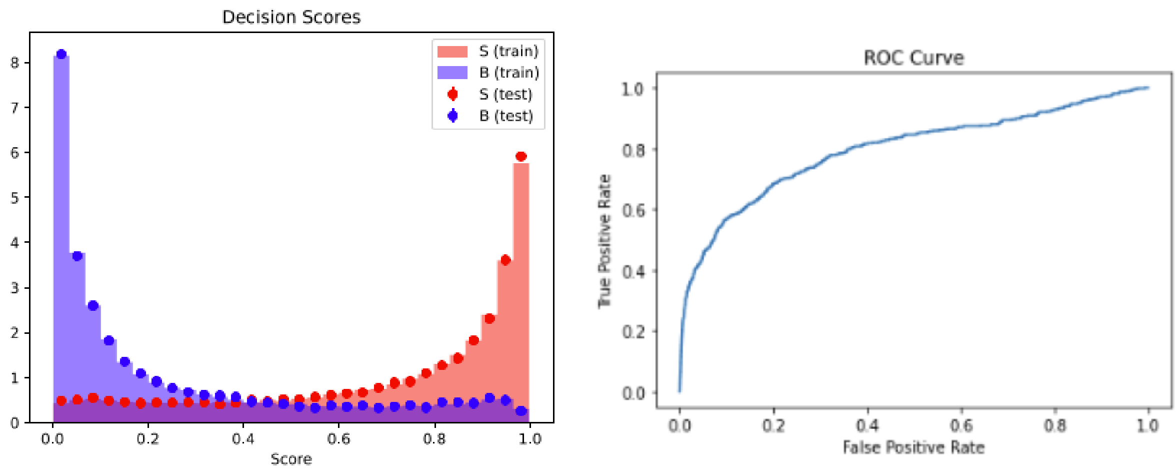

Figure 4: (*left*) Decision scores for BDT (*right*) ROC Curve

3 Conclusion

Searches for dark photons offer new opportunities to explore the Dark Sector fundamental structure and its connection to the Standard Model of known particles. In particular, the existence of a $H \to Z\gamma_D$ decay would be a clear signature of the "Higgs Portal" to the Dark Sector. The very preliminary results presented are the first tentative attempt at the LHC to search for such a signal. An extensive study of SM background processes is under way, as well as an optimisation of Machine Learning algorithms for new physics signal extraction using the ATLAS detector data collected in pp collisions at 13 TeV and 13.6 TeV.

References

[1] G. Aad, B. Abbott, D. C. Abbott, K. Abeling, S. H. Abidi, and et al., "Search for dark photons from higgs boson decays via zh production with a photon plus missing transverse momentum signature from pp collisions at $\sqrt{s} = 13$ tev with the atlas detector," *Journal of High Energy Physics*, vol. 2023, no. 7, jul 2023. [Online]. Available: http://dx.doi.org/10.1007/JHEP07(2023)133

[2] Aad, G. and Abbott, B. and Abbott, D. C. and Abeling, K. and Abidi, S. H. and et al., "Search for dark photons from higgs boson decays via zh production with a photon plus missing transverse momentum signature from pp collisions at $\sqrt{s} = 13$ tev with the atlas detector," *Journal of High Energy Physics*, vol. 2023, no. 7, 2023. [Online]. Available: https://doi.org/10.1007/JHEP07(2023)133

[3] J. Davies, "The Search for Dark Matter at the ATLAS Detector using Machine Learning," Ph.D. dissertation, Queen Mary, U. of London (main), Queen Mary, U. of London (main), 2025.