

A Recurrent Neural Network based algorithm to explore the VBF/VBS topology

VINCENZO DEL PIANO⁽¹⁾(²) ON BEHALF OF THE ATLAS COLLABORATION

⁽¹⁾ *Dipartimento di Fisica "Ettore Pancini", Università di Napoli "Federico II" - Napoli, Italy*

⁽²⁾ *INFN, Sezione di Napoli - Napoli, Italy*

Summary. — A Recurrent Neural Network based algorithm (VBF-RNN model) has been developed to explore the VBF(/VBS) topology in proton-proton collisions at the LHC. Starting from the seminal work developed for the full run-2 VV semi-leptonic resonant search (Eur. Phys. J. C 80 (2020) 1165 [1]) this tool shown the ability to largely improve the standard procedure used to tag VBF/VBS signature. This tagger can be readily employed across a broad spectrum of VBF/VBS topologies, eliminating the need for dedicated development by utilizing a pre-trained model well-suited to diverse use cases. Examples from ATLAS analyses - search for new resonances, SM Vector Boson scattering - based on the use of VBF-RNN will be presented showing the sensitivity improvement obtained using the VBF-RNN classification tool.

1. – Introduction

The production of two vector bosons through Vector Boson Scattering (VBS) and Vector Boson Fusion (VBF) mechanisms provides a unique opportunity to probe the electroweak structure of the Standard Model (SM) and to search for possible Beyond Standard Model (BSM) physics signals. These processes can be effectively classified using event-level information processed by algorithm based on Recurrent Neural Network (RNN). Previous applications [2, 1] have demonstrated the success of this approach in semi-leptonic final states, and ongoing studies aim to validate the model in other final-state topologies. This proceeding presents the physics motivations for exploring VBS and VBF topologies, the structure of the RNN-based classifier, recent analyses that demonstrate its performance and future developments.

2. – Physics Overview

Vector Boson Scattering (VBS) involves both the self-couplings of the gauge bosons and their coupling to the Higgs boson. It is therefore crucial for probing the non-Abelian gauge structure of the electroweak (EWK) sector of the Standard Model. Theories of

new phenomena beyond the SM (BSM) that foresee anomalous quartic gauge couplings (aQGC) or include the presence of additional resonances predict enhancements of VBS events at high transverse momentum (p_T) of the vector bosons and at high invariant mass of the diboson system. The aQGC can be studied in EWK diboson production by comparing measured cross sections to SM predictions [2]. Representative Feynman diagrams at tree level are shown in Fig.1.

Heavy resonances decaying into pairs of vector bosons (WW, WZ, ZZ — collectively referred to as VV, with $V = W, Z$) are predicted by several well-motivated extensions of the Standard Model (SM). These include the two-Higgs-doublet model, composite Higgs models, technicolor scenarios, and models with warped extra dimensions. Depending on the underlying theory, such resonances can be produced through different mechanisms, including gluon–gluon Fusion (ggF) and Vector Boson Fusion (VBF). In particular, ggF and VBF are of great interest: ggF proceeds via heavy quark loops and typically dominates in inclusive production, while VBF is characterized by the presence of two forward jets and limited hadronic activity in the central region, making it an important topology for searches targeting weakly interacting signatures. Representative Feynman diagrams of these production modes are shown in Fig. 2 [1].

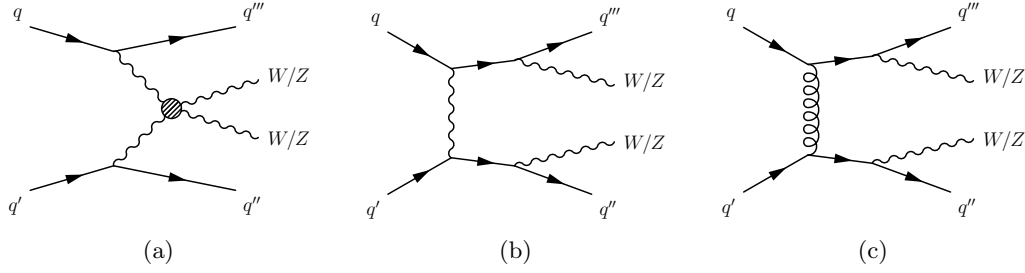


Fig. 1.: Representative Feynman diagrams for (a) EWK VVjj production via VBS, (b) EWK VVjj production via a non-VBS contribution, and (c) QCD VVjj production.

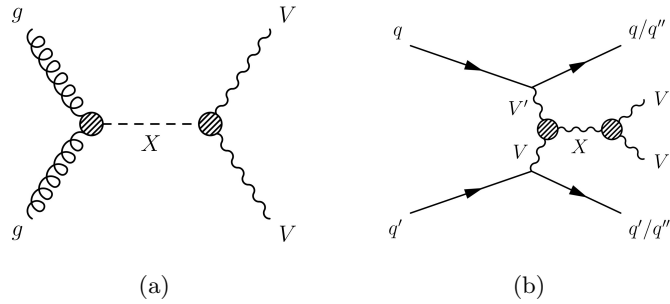


Fig. 2.: Representative Feynman diagrams, (a) Gluon-gluon fusion (ggF) and (b) Vector boson fusion (VBF), for the production of heavy resonances X with their decays into a pair of vector bosons. The hashed circles represent direct or effective couplings.

The experimental signatures of VBS and VBF processes are characterized, in addition to the presence of two vector bosons, by two forward jets with large separation in

pseudorapidity and high invariant mass of the dijet system. This is illustrated in Fig. 3, which shows the pseudorapidity (η) distribution of the additional jet with the highest p_T , for ggF and VBF production of a heavy scalar particle with $m = 1$ TeV.

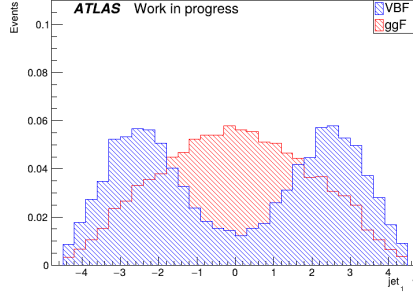


Fig. 3.: Distribution of the pseudorapidity η of the additional jet with the highest p_T in the semileptonic channel, for ggF and VBF production of a heavy scalar particle with $m = 1$ TeV.

3. – RNN-based algorithm

Recurrent Neural Networks (RNNs) are particularly well suited for processing sequential data of variable length, making them ideal for analyzing events with a varying number of jets without requiring fixed-size input formats. An RNN model has been developed to categorize event topologies associated with VBF, ggF, and VBS production mechanisms. The model, illustrated in Fig. 4a, is implemented using the Keras library with Theano as computational backend. The architecture consists of two hidden layers of Long Short-Term Memory (LSTM) units, each containing 25 cells. These layers enable the network to retain information along the jet sequence. The input features include the four-momenta of small-R jets (anti- k_T , $\Delta R = 0.4$), providing a detailed and flexible representation of each event. For VBF vs. ggF classification, the model uses only these four-momenta. In VBS analyses, designed as a binary signal-versus-background task, the input is extended to include both jet four-momenta and the number of associated tracks, enhancing sensitivity to forward jet characteristics. For VBS topologies in the merged regime, the architecture is augmented with an additional Deep Neural Network (DNN) branch, composed of fully connected layers, which processes large-R jet (anti- k_T , $\Delta R = 1.0$) information. The DNN output is combined with the LSTM output to form a hybrid model that captures both sequential and global features. The network's performance is illustrated by the ROC curves in Fig. 4b, showing its ability to discriminate between signal and background. The network was specifically trained to distinguish electroweak production of two vector bosons in association with two jets from Standard Model backgrounds [2]. A more detailed description of the signal model and analysis context is provided in the section 4. The output of the model is a single RNN score, a continuous variable ranging from 0 to 1.

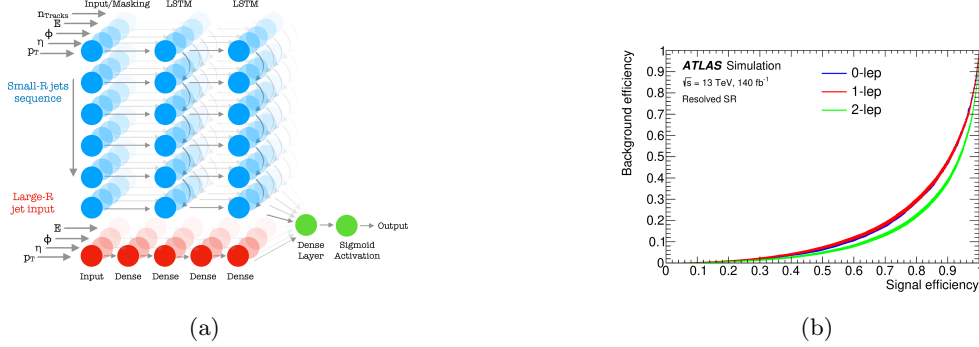


Fig. 4.: (a) Network architecture used in the VBS analysis in the merged regime [2]; (b) Receiver Operating Characteristic (ROC) curves for signal and background samples used in the VBS analysis [2].

4. – RNN-based algorithm application

Vector Boson Fusion. The RNN-based tool is used for the first time in a search for heavy resonances X in the mass range from 300 GeV to 5 TeV, decaying into diboson final states ($X \rightarrow VV$) in pp collisions at $\sqrt{s} = 13$ TeV with an integrated luminosity of 139 fb $^{-1}$ [1]. The network was specifically trained on simulated events of a 1 TeV scalar resonance decaying via $X \rightarrow ZZ \rightarrow \ell\ell qq$, in order to optimally discriminate this signal from the background. Three types of diboson resonances are considered in this search:

- A neutral scalar resonance, the radion (R), predicted in some Randall–Sundrum (RS) models, which can decay into WW or ZZ .
- Heavy versions of the SM W and Z bosons, denoted as W' and Z' , as described in the Heavy Vector Triplet (HVT) framework. These can decay as $W' \rightarrow WZ$ and $Z' \rightarrow WW$.
- A spin-2 graviton (G_{KK}), the first Kaluza–Klein (KK) excitation in a bulk RS model, decaying into WW or ZZ .

Figure 5a compares the RNN score of simulated events from VBF and ggF production of a 1 TeV resonance in the signal models considered in this search. An event is classified as a VBF event if its RNN score is above 0.8 otherwise as a ggF event [1]. The use of the RNN classifier allows recovery of signal events where only one VBF-tagged jet is reconstructed (approximately 30% of signal events), which were previously not selected in standard searches requiring two VBF-tagged jets [1]. Figure 5b shows the observed and expected upper limits at 95% confidence level (CL) as functions of its mass for both the ggF and VBF processes.

Vector Boson Scattering. Electroweak production of diboson pairs (WW , WZ , ZZ) in association with a high-mass dijet system, where one boson decays leptonically and the other hadronically, has recently been observed with a significance greater than 5σ , based on data corresponding to an integrated luminosity of 140 fb $^{-1}$. To enhance the separation between signal and background processes, an RNN-based tool has been employed. The

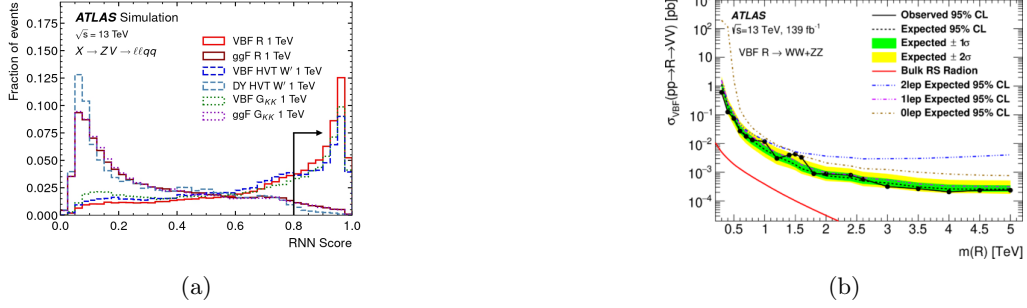


Fig. 5.: (a) RNN score distributions for the production of a 1 TeV resonance in the signal models considered for this search [1]; (b) Observed (black solid curve) and expected (black dashed curve) 95 CL upper limits on the VBF production cross-section of an RS radion at $\sqrt{s} = 13$ TeV in its diboson (WW and ZZ) decay mode as functions of the RS radion mass, combining the $R \rightarrow WW$ and $R \rightarrow ZZ$ searches in the three leptonic channels.

architecture of the network, illustrated in Fig. 4a, is specifically designed to classify signal and Standard Model background events. Figure 6a shows the distributions of the RNN score for signal and background samples, comparing training (histograms) and test (markers) datasets and Figure 6b the comparison between observed data and the expected contributions from signal and background. The RNN score is used as the final discriminating variable in the statistical analysis. The background-only hypothesis is excluded with an observed significance of 7.4σ , while the expected significance is 6.1σ .

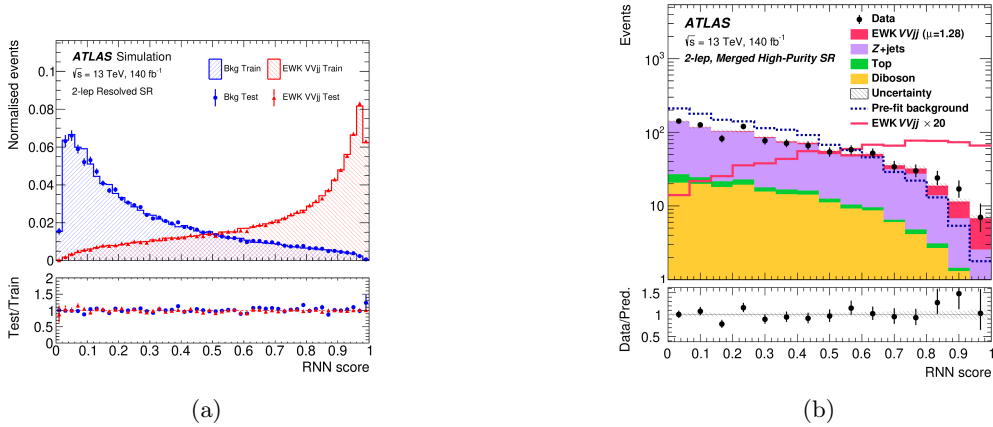


Fig. 6.: (a) RNN score distributions for signal and background samples showing the training (histograms) and test (markers) datasets used in the training phase; (b) Comparison between observed data and expected signal event and background [2].

5. – Conclusion and Future Applications

Several studies are ongoing to extend the use of the RNN classifier to other VBF/VBS final states. Thanks to its flexibility and input-level design, the RNN-based tool can be seamlessly adapted to a wide variety of VBF/VBS processes. One of the next applications, currently under testing, concerns the study of double Higgs production. For processes with small cross sections and limited statistics, this tool may offer a significant advantage over conventional approaches. Figure 7a shows the RNN score distribution for ggF and VBF signals in fully hadronic final states, with the network trained on a semi-leptonic channel. This setup is intended to provide a first test of the network’s ability to generalize across different final states. Figure 7b presents a first performance evaluation of the RNN in the context of double Higgs (hh) production in the $4b$ final state [3].

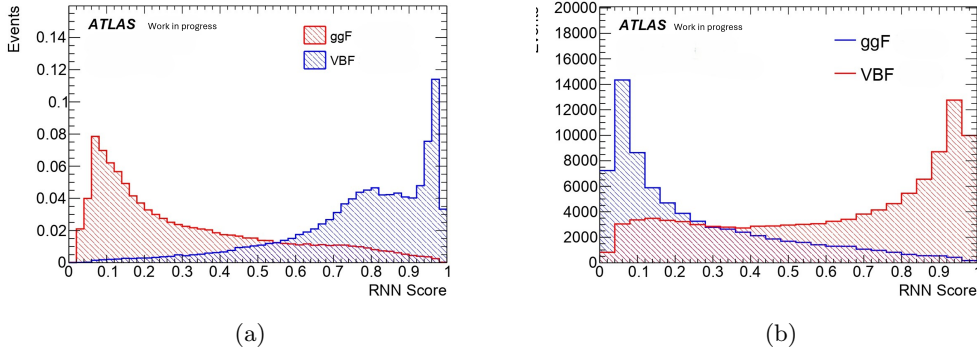


Fig. 7.: The network is trained on a semi-leptonic channel and tested on the fully hadronic final state. (a) Distribution of the RNN score for ggF and VBF signals in Higgs production with $m_H = 3 \text{ TeV}$; (b) distribution of the RNN score for ggF and VBF signals in di-Higgs (hh) production.

REFERENCES

- [1] ATLAS COLLABORATION, *Search for heavy diboson resonances in semileptonic final states in pp collisions at $\sqrt{s} = 13 \text{ TeV}$ with the ATLAS detector*, *Eur. Phys. J. C*, (2020) 1–20.
- [2] ATLAS COLLABORATION, *Electroweak diboson production in association with a high-mass dijet system in semileptonic final states from pp collisions at $\sqrt{s} = 13 \text{ TeV}$ with the ATLAS detector*, *Submitted to: EPJC*, (2025) 1–21.
- [3] ATLAS COLLABORATION, *Search for pair production of boosted Higgs bosons via vector-boson fusion in the $b\bar{b}b\bar{b}$ final state using pp collisions at $\sqrt{s} = 13 \text{ TeV}$ with the ATLAS detector*, *Phys. Lett. B*, (2024) 1–20.
- [4] G. Aad *et al.* [ATLAS], “The ATLAS Experiment at the CERN Large Hadron Collider,” *JINST* **3**, S08003 (2008) doi:10.1088/1748-0221/3/08/S08003