Using Convolutional Neural Network to Identify Signals of the Rare Beauty-meson Decay

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1. Introduction

The universality of lepton flavour (LFU) is an interesting accidental symmetry in the Standard Model (SM), which states that the couplings of a lepton to all types of gauge bosons are the same for all flavours in the SM. A violation of LFU will definitely lead physics to a new era.

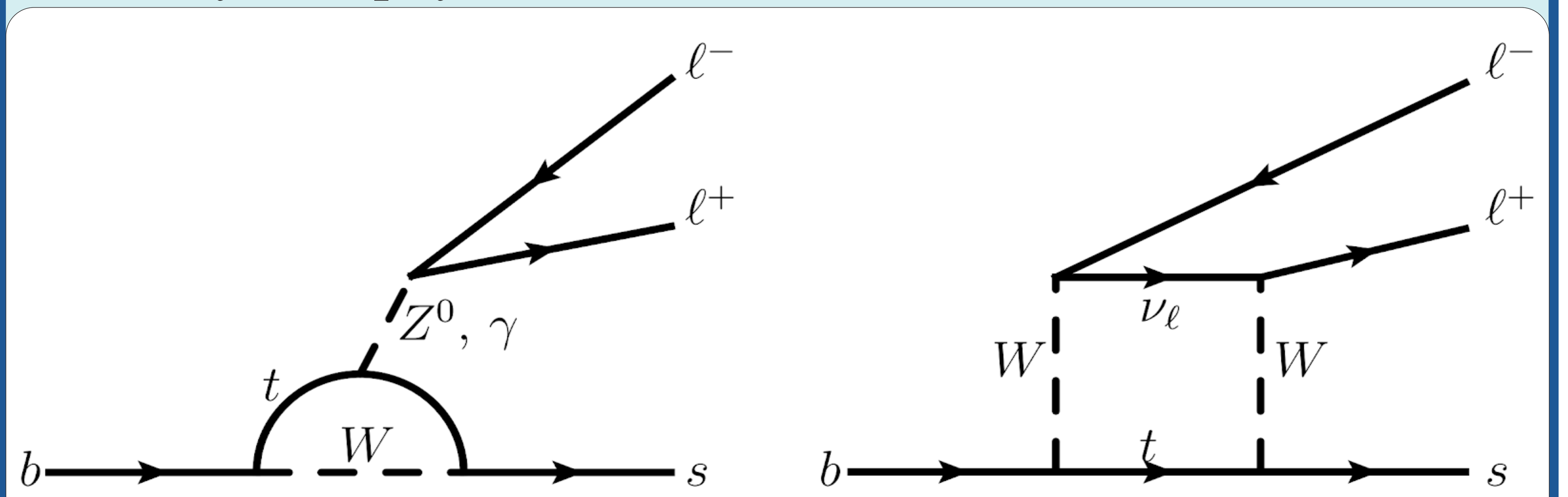

Fig .1. The Feynman diagram of the Standard Model *b->s l+l-* decay.[1]

The B-meson is composed of a bottom quark and a up/down/strange/charm quark. The rare decay modes of heavy B-meson were studied in collaborations such as LHCb, BaBar and CMS. It is observed that the ratios of branching fractions of decay products with different flavours have shown discrepancies with the SM and the results implied a violation of the LFU.

The current best limit of the branching fraction of $b \rightarrow s\tau\tau$ decay is 2×10^{-3}[2]. The aim of our project is to try to push this limit further using the Convolutional Neural Network (CNN) Algorithm. In this project, we used the data corresponding to an integrated luminosity of 1.8 fb^{-1} of pp collisions recorded by the LHCb experiment in 2018, and also the simulated Monte Carlo (MC) signals for $B_s \rightarrow \phi_3\tau\tau$ and $B_s \rightarrow \phi\mu\mu$ decays.

2. Objectives

- Only input the information of raw tracks of the visible particles (B meson, μ+ and μ-) to train CNN models;
- Aim to find other discriminative powers that have not been distinguished by the Boosted Decision Tree (BDT) Algorithm used previously;
- Analyse the performance of 2D CNN models, compare it with the BDT method and evaluate whether upgrading to 3D CNN models will further improve the result.

3. CNN

--- Why CNN? ---

- Want to look at the geometry of the rare decay;
- High efficiency; reduce the amount of neurons without losing the image's characteristics.

--- How Does It Work? ---

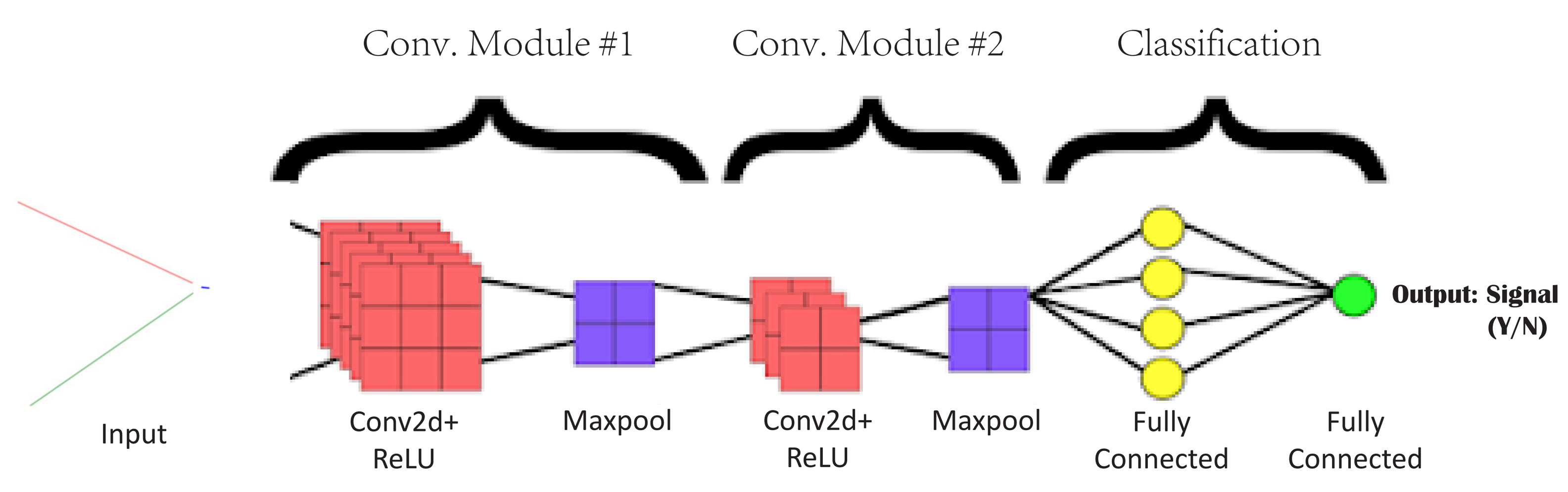

Fig .2. A schematic diagram of the CNN.[3]

- Signal MC as signal input, labelled as 1;
- ϕ-$\mu\mu$ MC and Background proxies as false signal input, labelled as 0;
- For each event, project the line of flights of the B meson and the muon pair to *XY/ XZ/ ZY* plane;
- Use 80% of the above data to train CNN and the rest 20% for cross validation;

	Loss	Accuracy	Validation Loss	Validation Accuracy
XY Plane	0.2629	0.8934	0.2616	0.8905
XZ Plane	0.3355	0.8633	0.3548	0.8616
ZY Plane	0.2822	0.8937	0.3003	0.8827

Tab .1. This table presents the accuracy and loss values of the trained CNN model of 3 different planes.

- After training, CNN can identify whether a given event is a signal by outputting a probability between 0 (not signal) and 1(signal).

Reference

[1] Humair.T. *Testing lepton universality in penguin decays of beauty mesons using the LHCb detector.* Imperial College London; 2019

[2] Panella.E. *Searching for $b \rightarrow s\tau+\tau-$ Decays.* Presentation presented at: Imperial College London; 2020

[3] Dumane.G. *Introduction to Convolutional Neural Network (CNN) using Tensorflow* [Internet]. Medium. 2021 [cited 26 February 2021]. Available from: https://towardsdatascience.com/introduction-to-convolutional-neural-network-cnn-de73f69c5b83

4. Results & Discussion

- CNN has successfully discriminated against backgrounds to a high accuracy;
- The performance is compatible with BDT;
- Need to use CNN outputs as BDT inputs to discriminate the experimental data and calculate the ratio of branching fraction;
- Could potentially use 3D plots to train CNN, as it will give more information than 2D plots, however it is very computationally heavy.

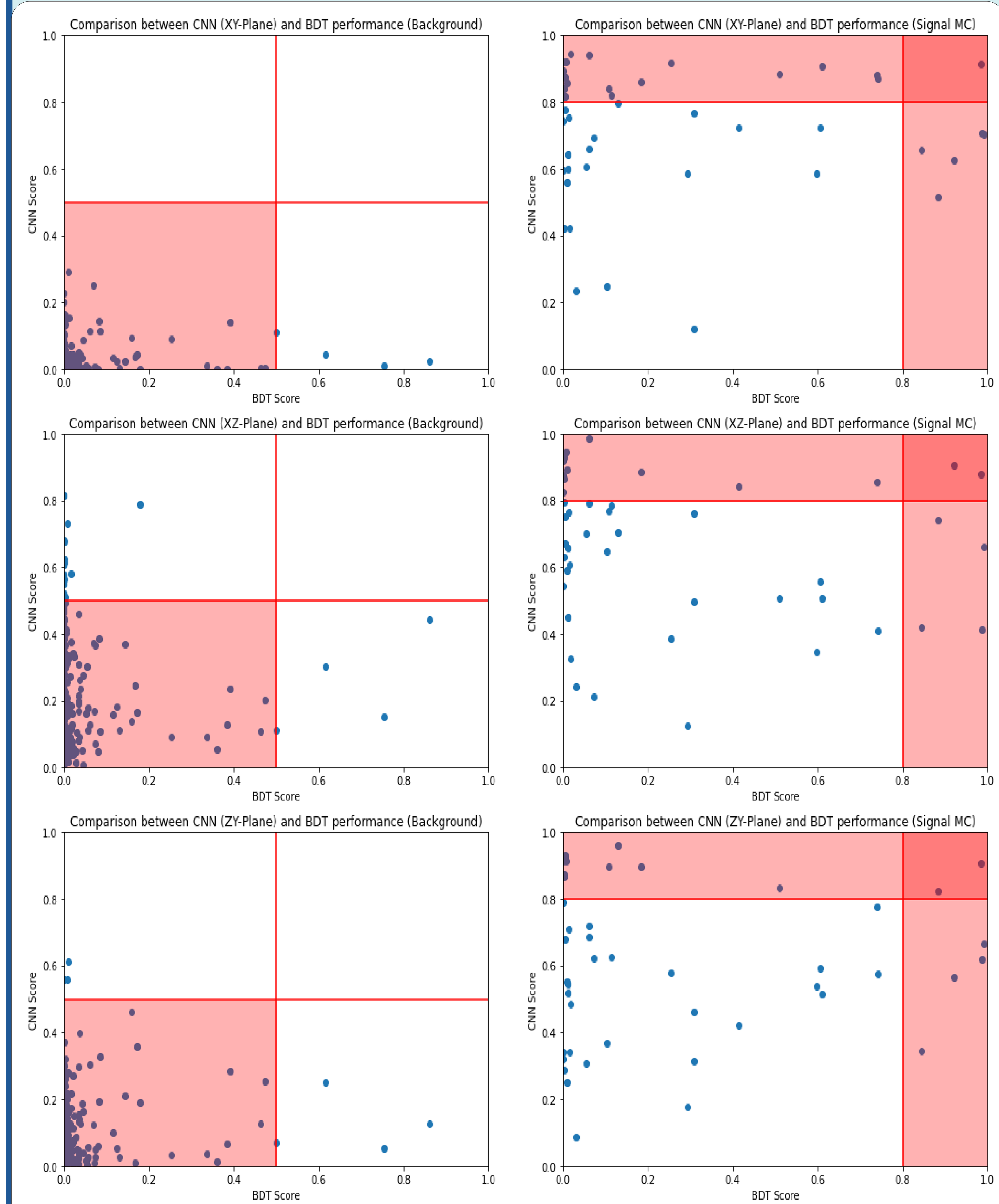

Fig . 3. Performance comparisons between BDT and CNN on background (left) and signal Monte Carlo samples (right) respectively. The background region (below 0.5) and the signal region (above 0.8) are highlighted in red respectively.