

EXPLORING THE PERFORMANCE OF DEEP LEARNING IN HIGH- ENERGY PHYSICS

ORGANIZAN
cedia • UCUENCA

José Ochoa, Daniela Merizalde, Xavier Tintin, Edgar
Carrera, Diana Martínez, David Mena

TIC2023
ec11TH

SÉ
PARTE
DE

10-18-2023

Deep Learning in high energy physics | José Ochoa.
Universidad San Francisco de Quito

Table of contents

1. Introduction
2. Methodology
3. Results
4. Conclusions

Introduction

The universe we see and how to "break" it

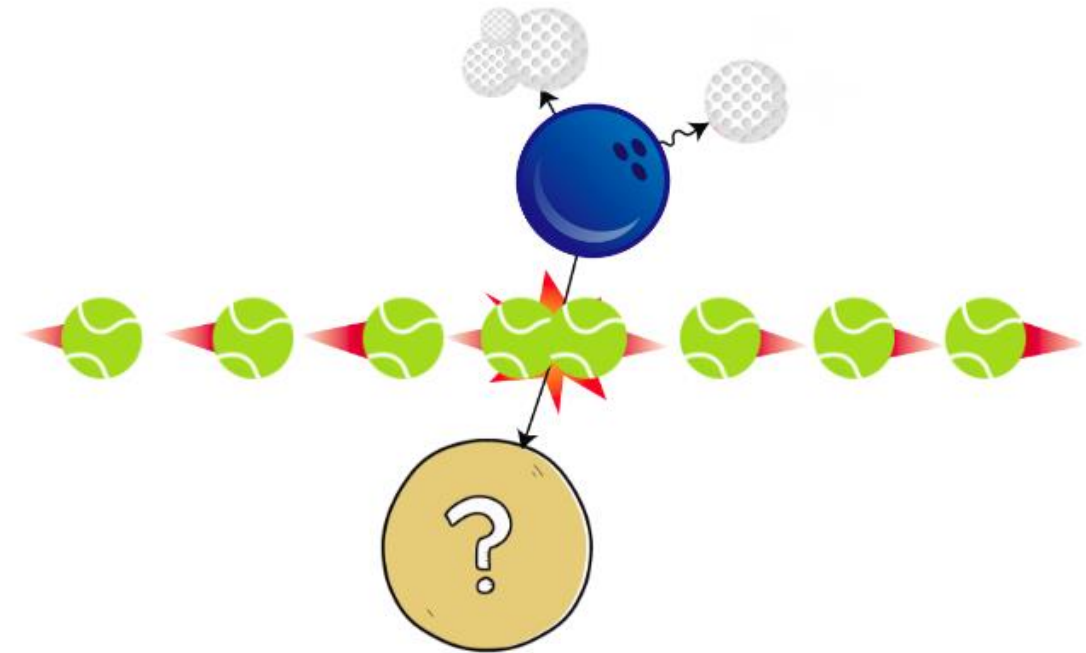
Standard Model of Elementary Particles

	three generations of matter (fermions)			interactions / force carriers (bosons)	
	I	II	III		
mass	$\approx 2.2 \text{ MeV}/c^2$	$\approx 1.28 \text{ GeV}/c^2$	$\approx 173.1 \text{ GeV}/c^2$	0	$\approx 124.97 \text{ GeV}/c^2$
charge	$\frac{2}{3}$	$\frac{2}{3}$	$\frac{2}{3}$	0	0
spin	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	1	0
QUARKS	u up	c charm	t top	g gluon	H higgs
	d down	s strange	b bottom	γ photon	
LEPTONS	$\approx 0.511 \text{ MeV}/c^2$	$\approx 105.66 \text{ MeV}/c^2$	$\approx 1.7768 \text{ GeV}/c^2$	$\approx 91.19 \text{ GeV}/c^2$	
	-1	-1	-1	0	
	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	1	
	e electron	μ muon	τ tau	Z Z boson	
	$< 1.0 \text{ eV}/c^2$	$< 0.17 \text{ MeV}/c^2$	$< 18.2 \text{ MeV}/c^2$	$\approx 80.360 \text{ GeV}/c^2$	
	0	0	0	± 1	
	ν_e electron neutrino	ν_μ muon neutrino	ν_τ tau neutrino	W W boson	
	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	1	

SCALAR BOSONS

GAUGE BOSONS
VECTOR BOSONS

$$E = mc^2$$



LHC and CMS

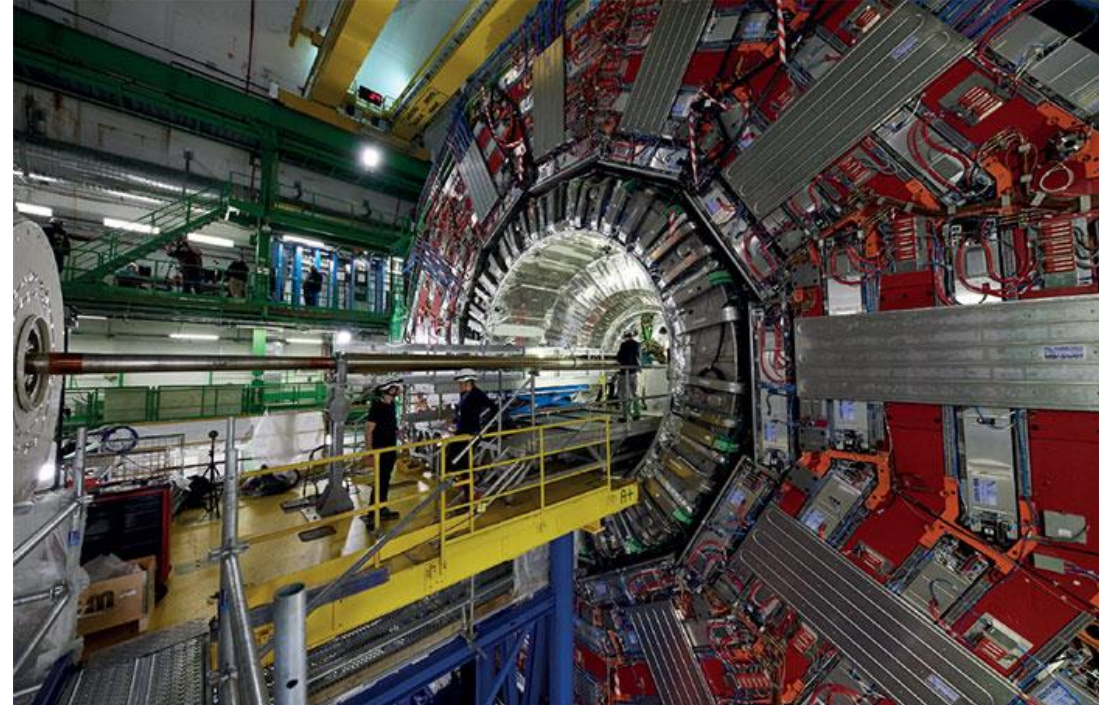
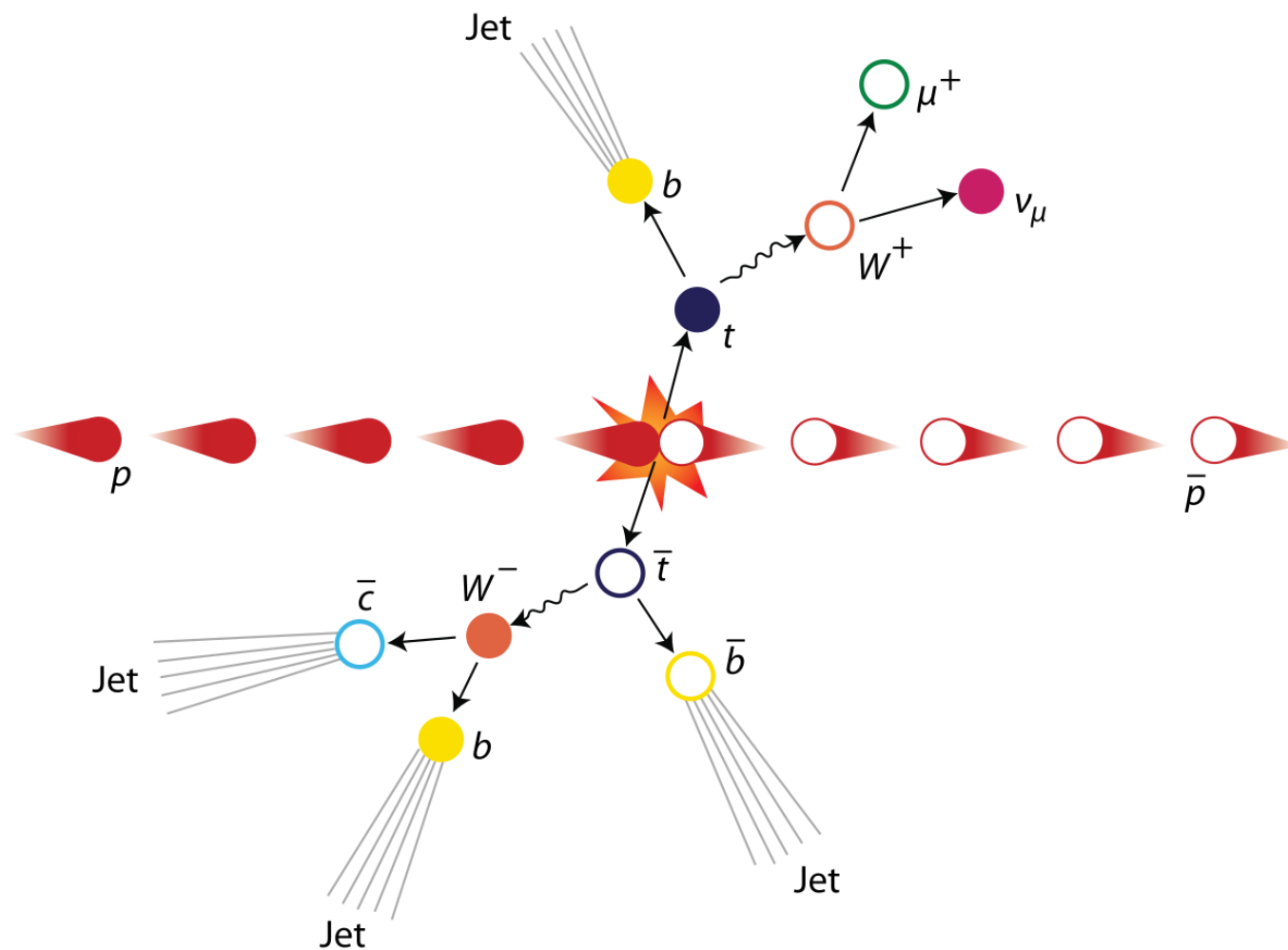


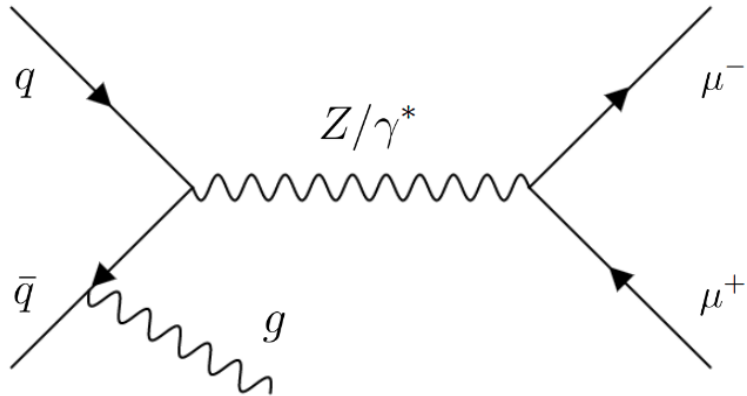
Fig 1: Distribution of the different detectors at LHC and the CMS detector[1]

A physics process

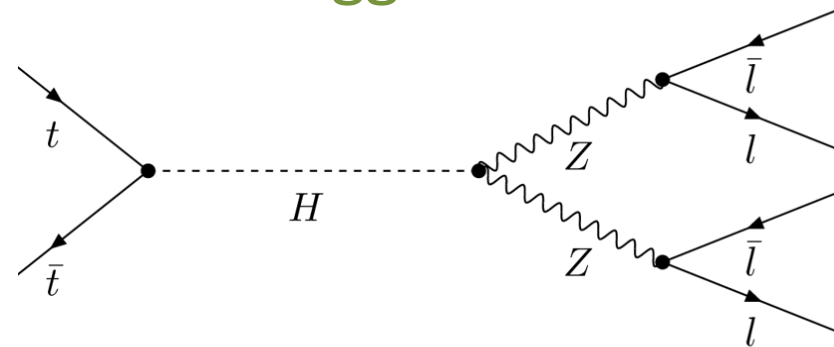


The DHJW scenario

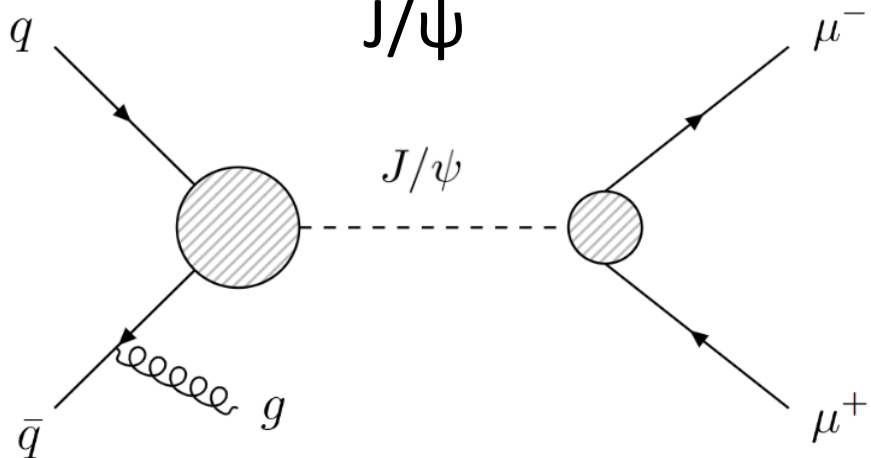
Drell-Yan



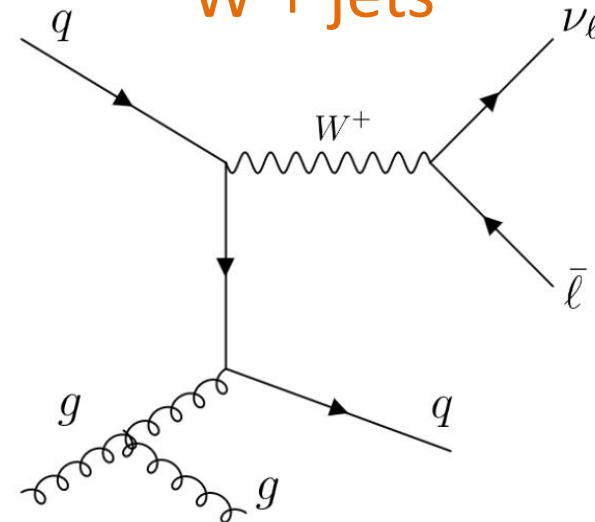
Higgs



J/ψ

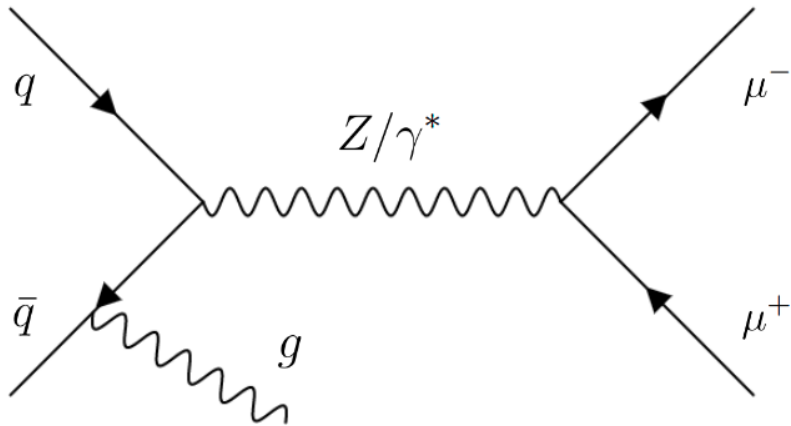


W + jets

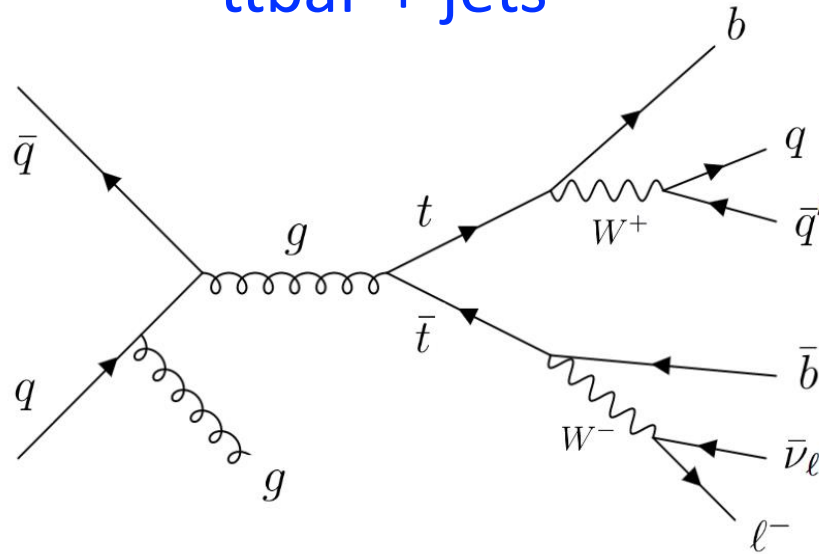


DTW scenario

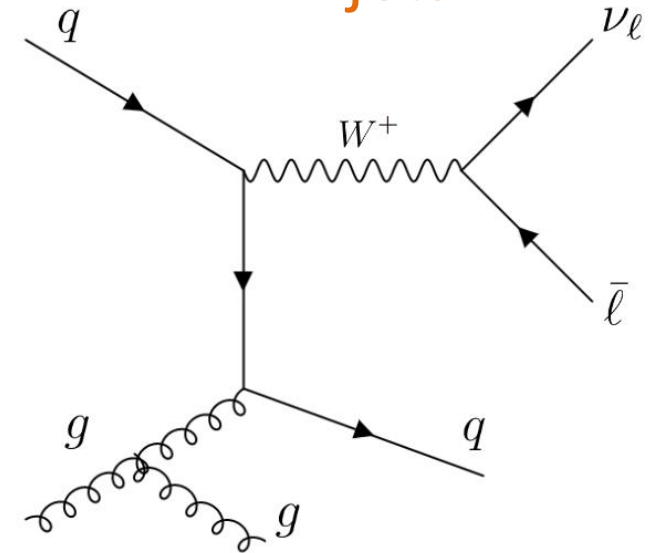
Drell-Yan



$t\bar{t}$ + jets



W + jets



General Approach

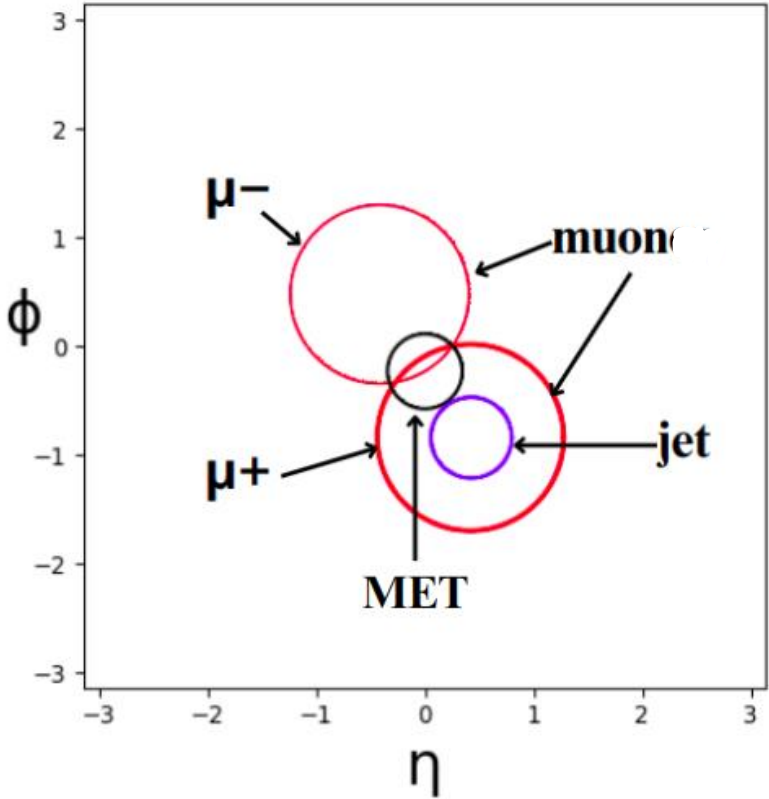
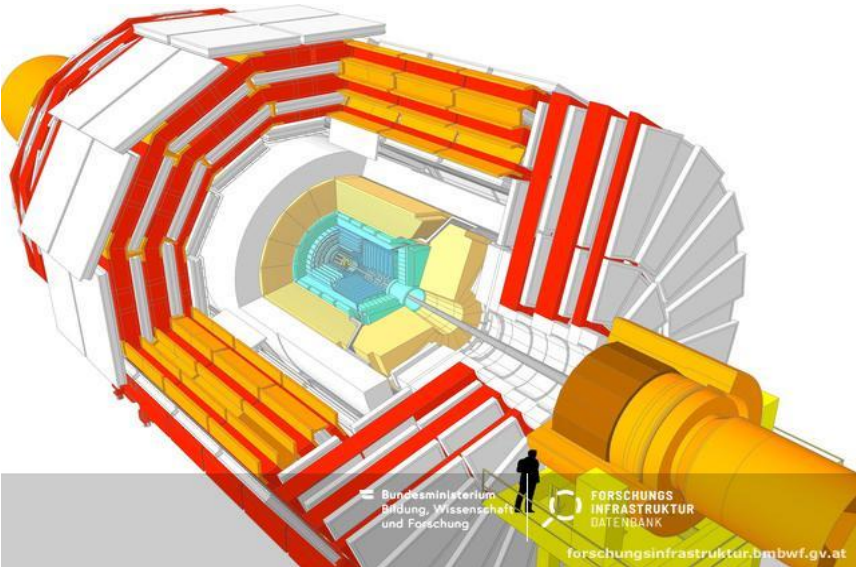
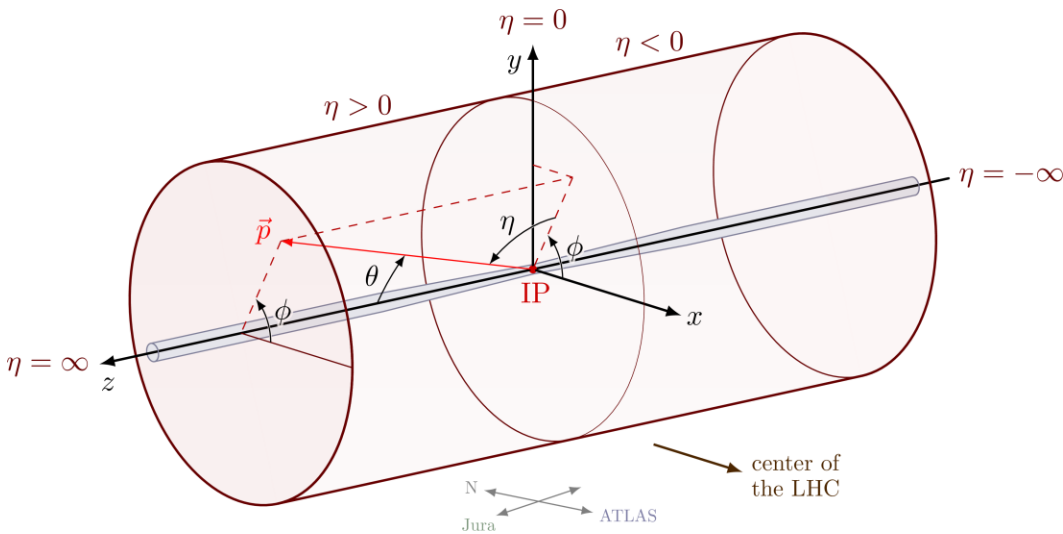
1. Extract relevant information from CERN Open Data Portal
2. Use that information to generate images (two scenarios)
3. Use the images to train various CNN's architectures
4. The trained neural network with the best performance metric is employed to classify real collision data

Methodology

Data collection and information extraction

- The datasets used correspond to the simulation and real data obtained in 2015 during CMS Run II at 13 TeV. Open Data
- Muons, jets, MET

Image Generation



$$p_T = \sqrt{p_x^2 + p_y^2} \quad R = \alpha \cdot \ln p_T$$

DHJW

Dataset	Number of Jets	Number of Images
A	0	110796
B	1	110796
C	2	64028

Table 1: Number of jets and number of images presented on Datasets A, B and C.

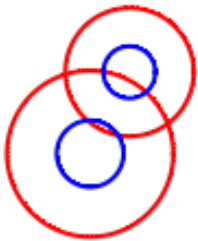
DTW

Dataset	Number of Jets	Number of Images
D	1	83097
E	2	83097
F	3	83097
G	4	83097

Table 2: Number of jets and number of images presented on Datasets D, E, F and G

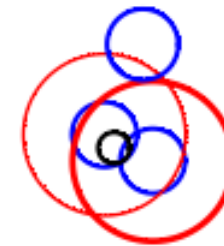
DHJW

- No MET or Muon charge information
- Constant Jets across the images

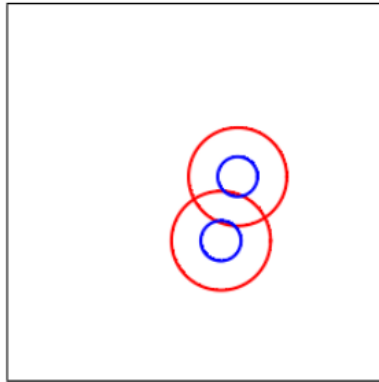


DTW

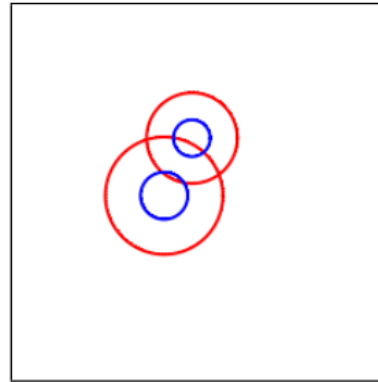
- MET and Muon charge information
- Variable number of Jets across the images



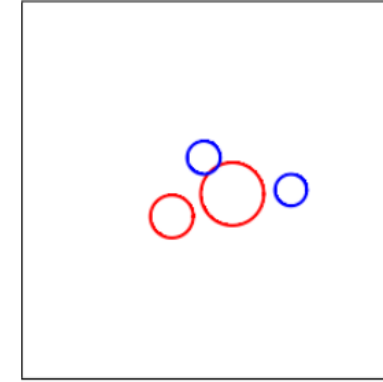
DHJW Images



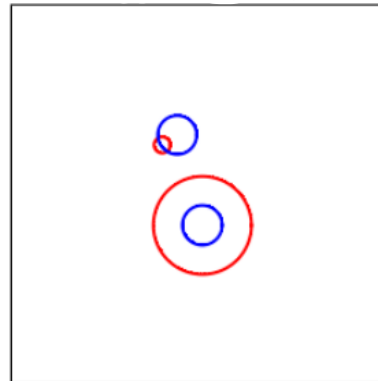
Drell-Yan



Higgs



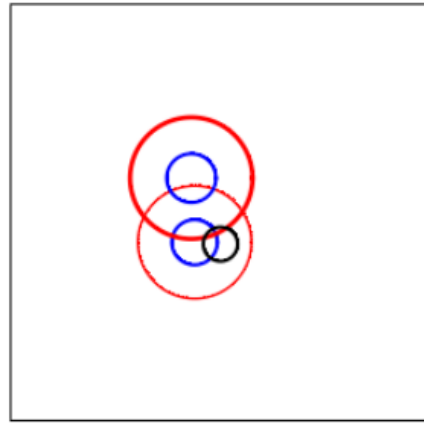
J/ψ



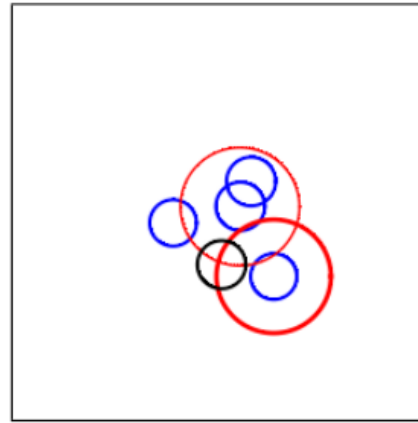
W + jets

Fig 3: Example of images belonging to dataset C

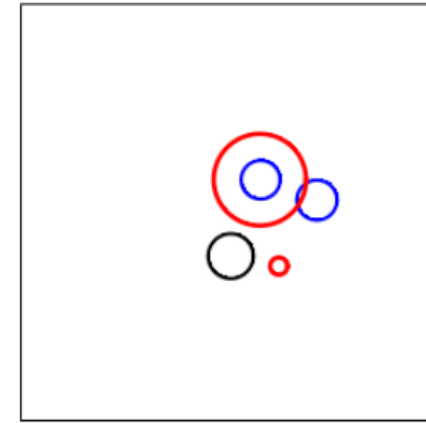
DTW Images



Drell-Yan



$T\bar{t}$ + jets



W + jets

Fig 3: Example of images belonging to dataset G

Types of Neural Network

- ResNet 50
- DenseNet
- InceptionV3
- MobileNet V2

Evaluating each model's accuracy, loss and F1 score sets foreword the most suitable model when classifying high-energy particle collision outcomes.

Training process and Evaluation Metrics

- 40 epochs with early stopping.
- Adam optimization algorithm and Softmax Loss
- The training and testing of the CNN models were conducted on Google Colaboratory using A100 GPU hardware accelerators.
- All the code can be found in <https://github.com/jose8af/cnn-hep-thesis> [4]

Results

DHJW

Dataset	Test Acc	Test Loss
A	0.7209	0.7463
B	0.7322	0.6944
C	0.7956	0.5148

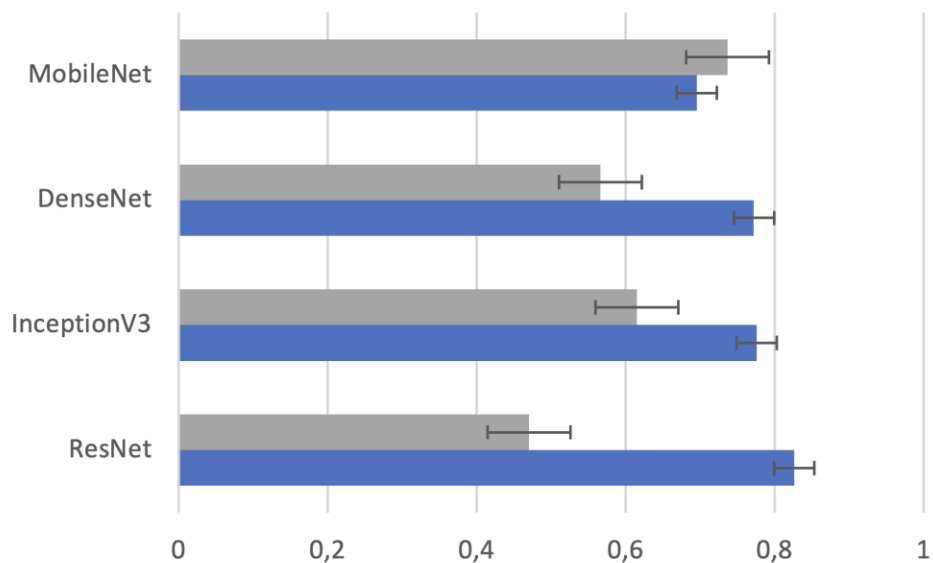
Table 3: Accuracy and loss value of the DHJW datasets

DTW

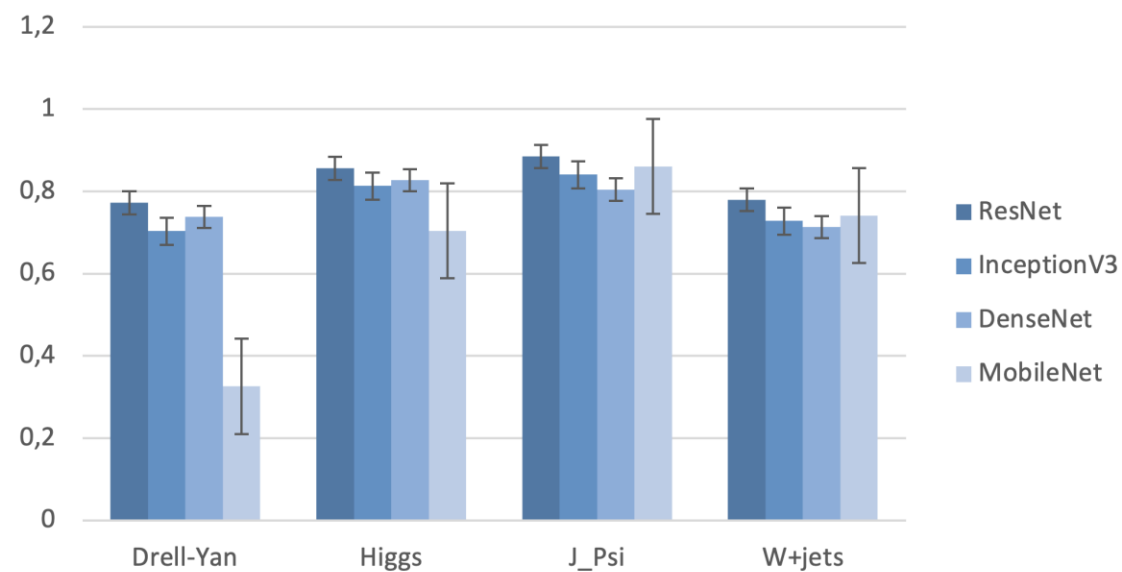
Dataset	Test Acc	Test Loss
D	0.8012	0.4508
E	0.8208	0.4185
F	0.8355	0.3875
G	0.8416	0.3681

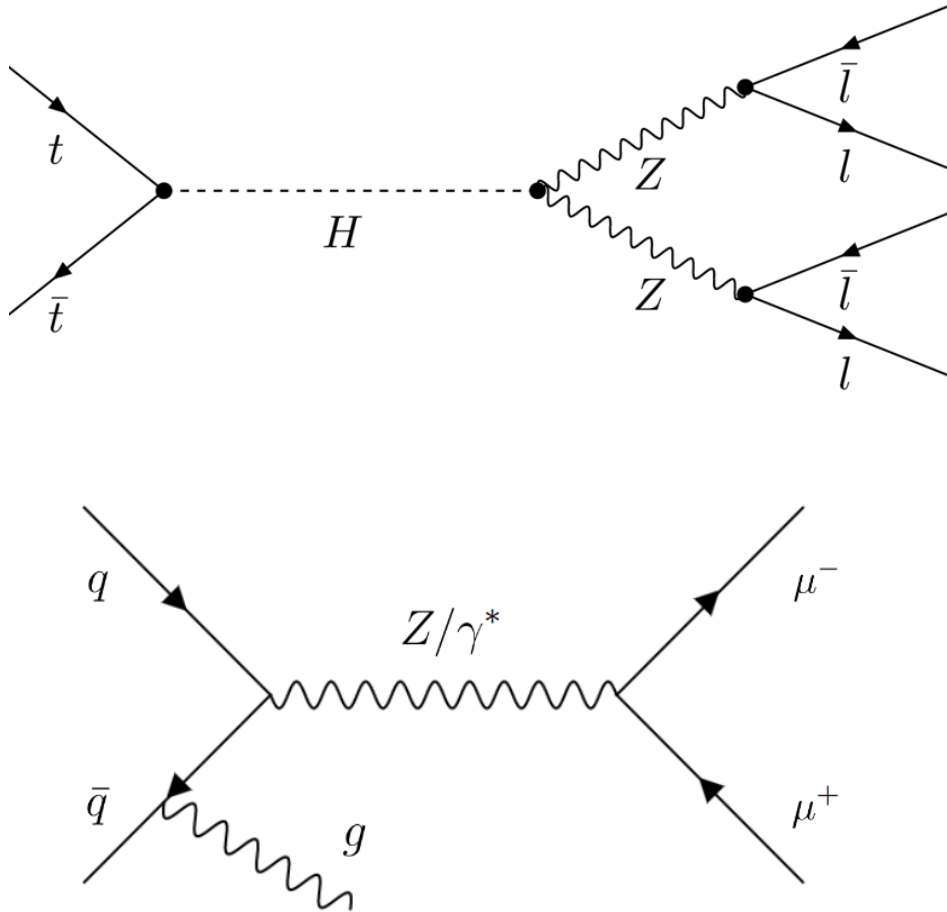
Table 4: Accuracy and loss value of the DTW datasets

Metrics



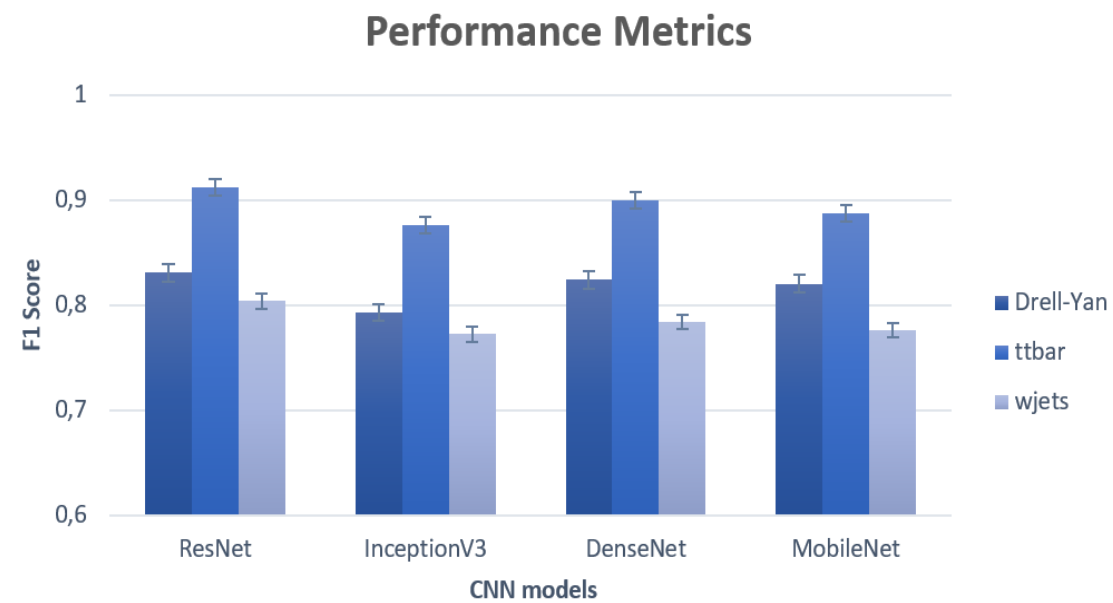
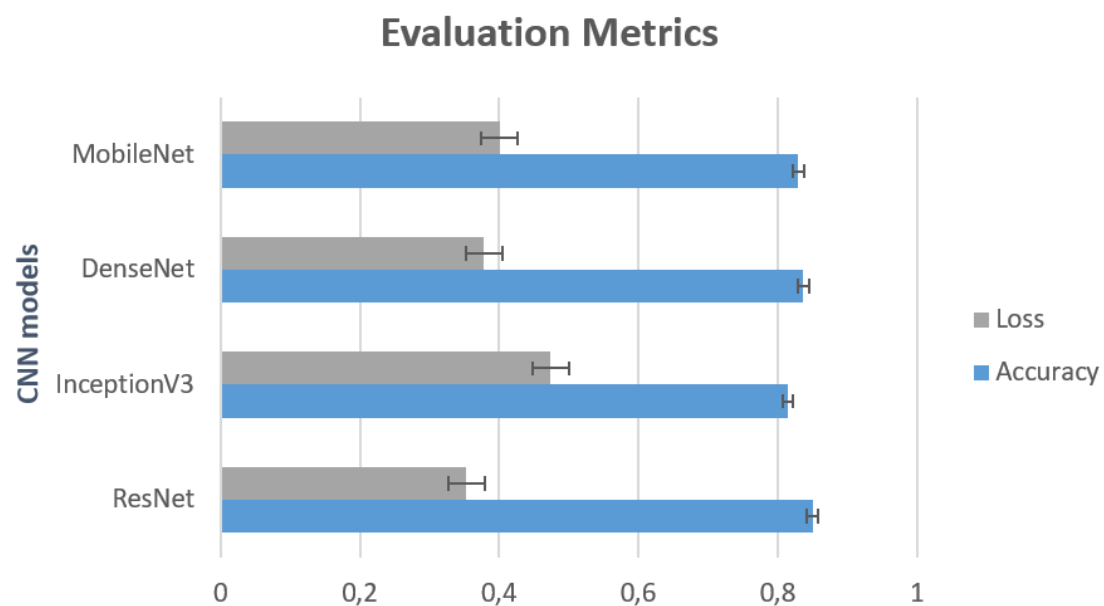
F1 Score

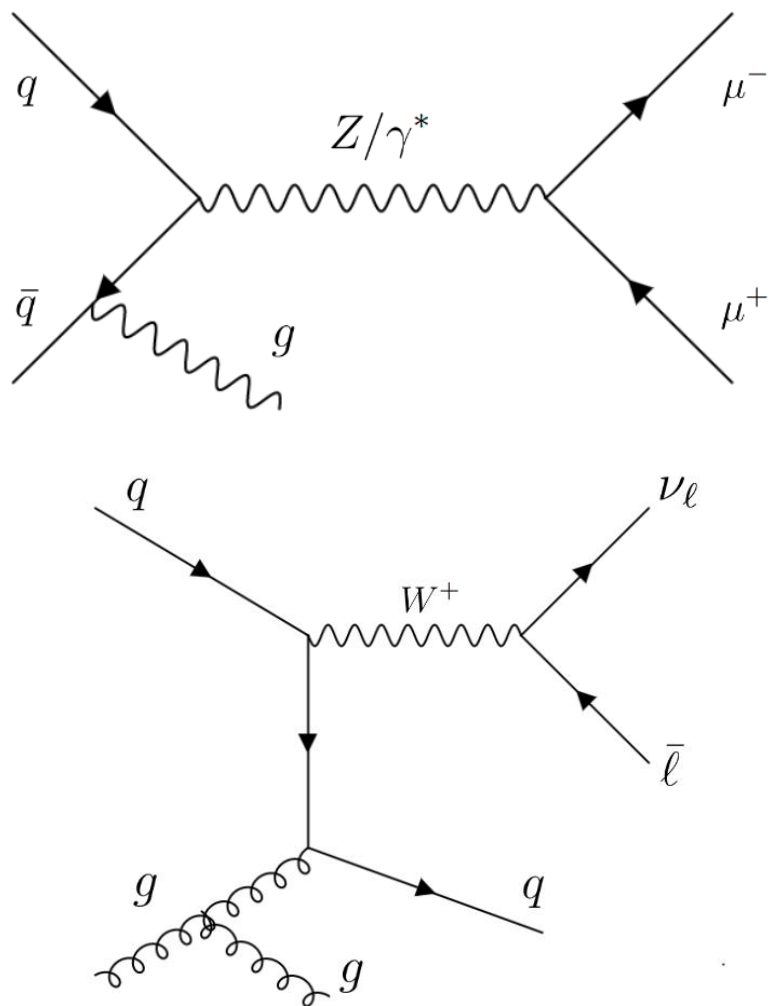




Actual Class	Drell-Yan	0.67	0.20	0.02	0.12
	Higgs	0.03	0.93	0.00	0.04
	J_Psi	0.01	0.00	0.92	0.07
	W+jets	0.02	0.04	0.14	0.79
		Drell-Yan	Higgs	J_Psi	W+jets
Predicted Class					

Fig 4: Confusion matrices of the best model





Actual Class	Predicted Class		
	drellyan	ttbar	wjets
drellyan	0.74	0.04	0.22
ttbar	0.00	0.98	0.02
wjets	0.04	0.15	0.81

Fig 5: Confusion matrices of the best model

Application of the model in real collision data

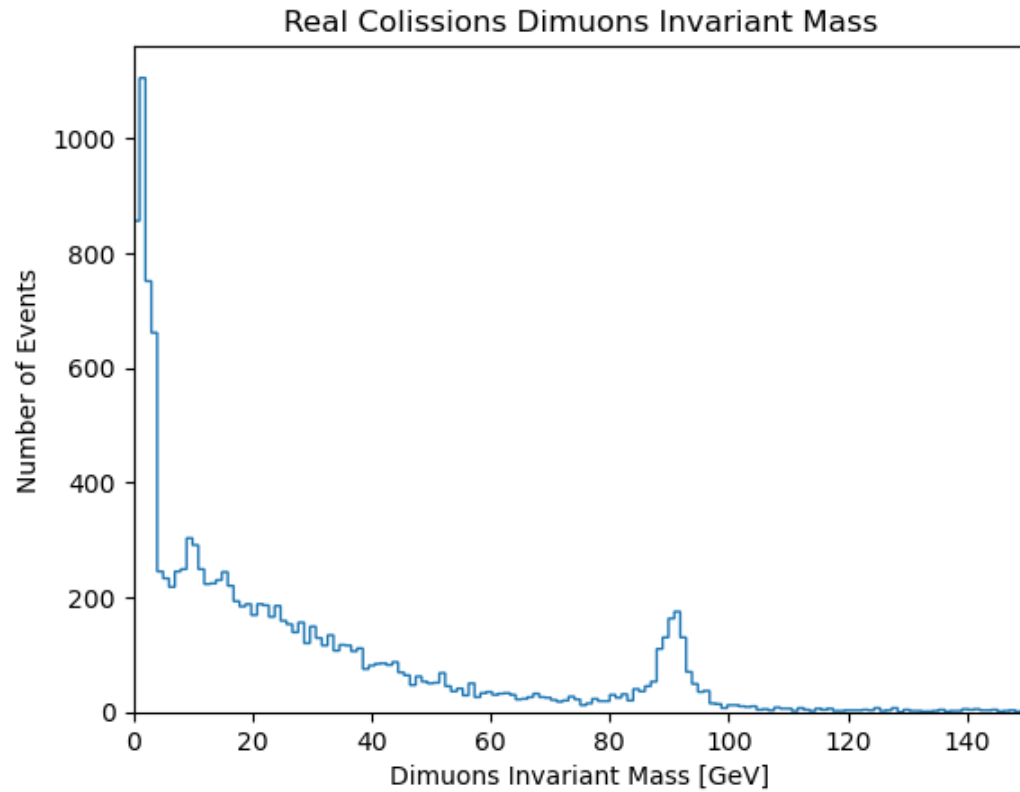
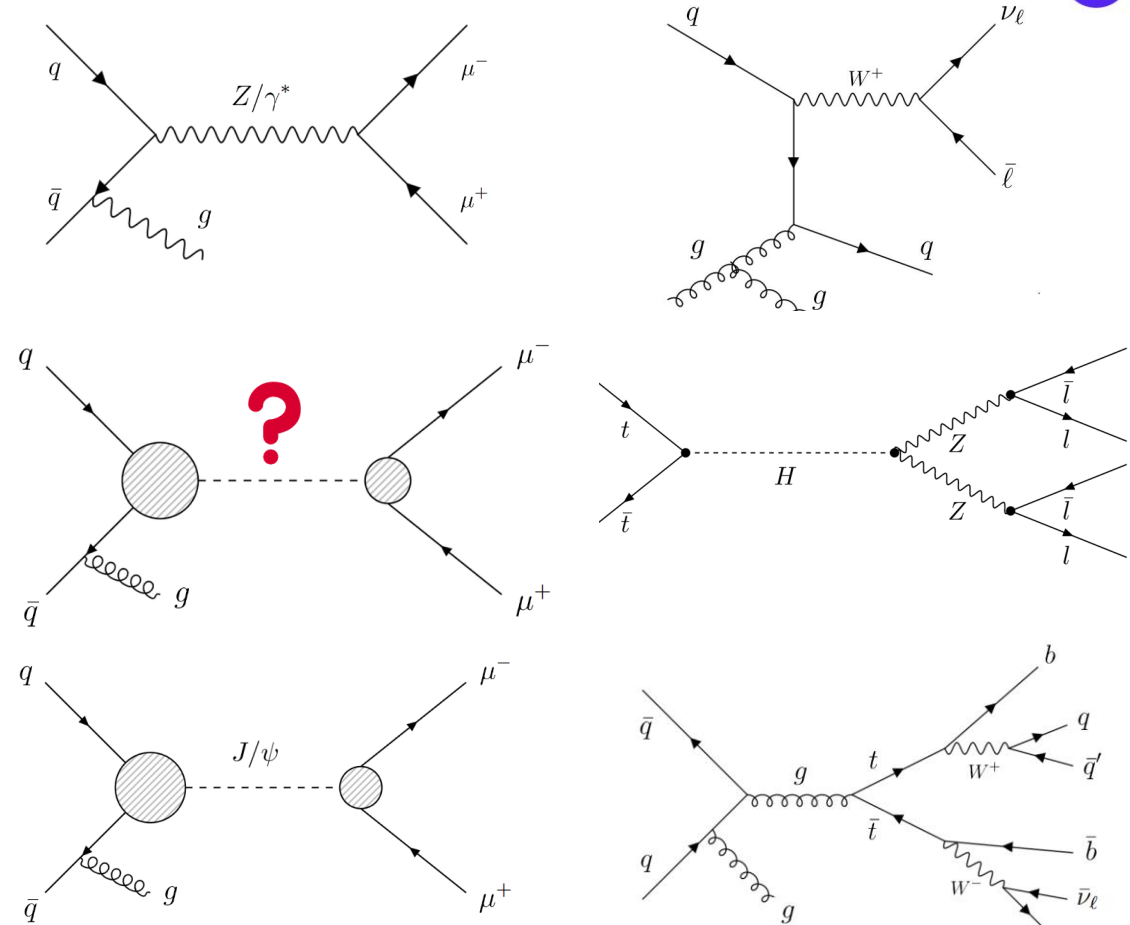


Fig 6: Dimuon invariant mass of real collision data



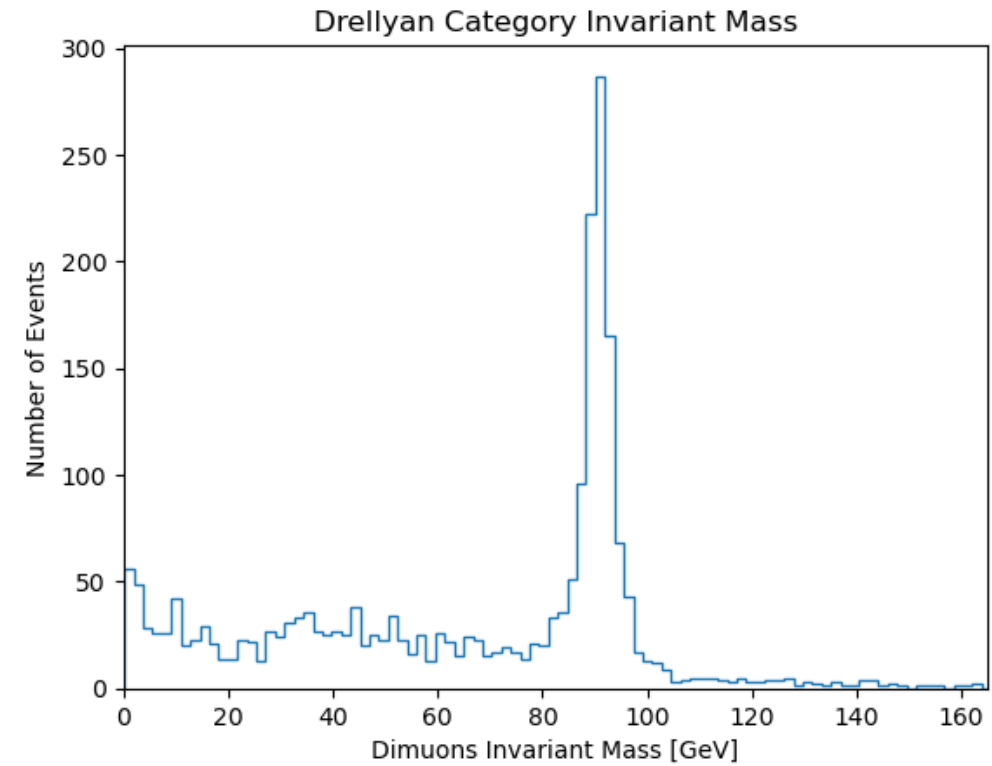
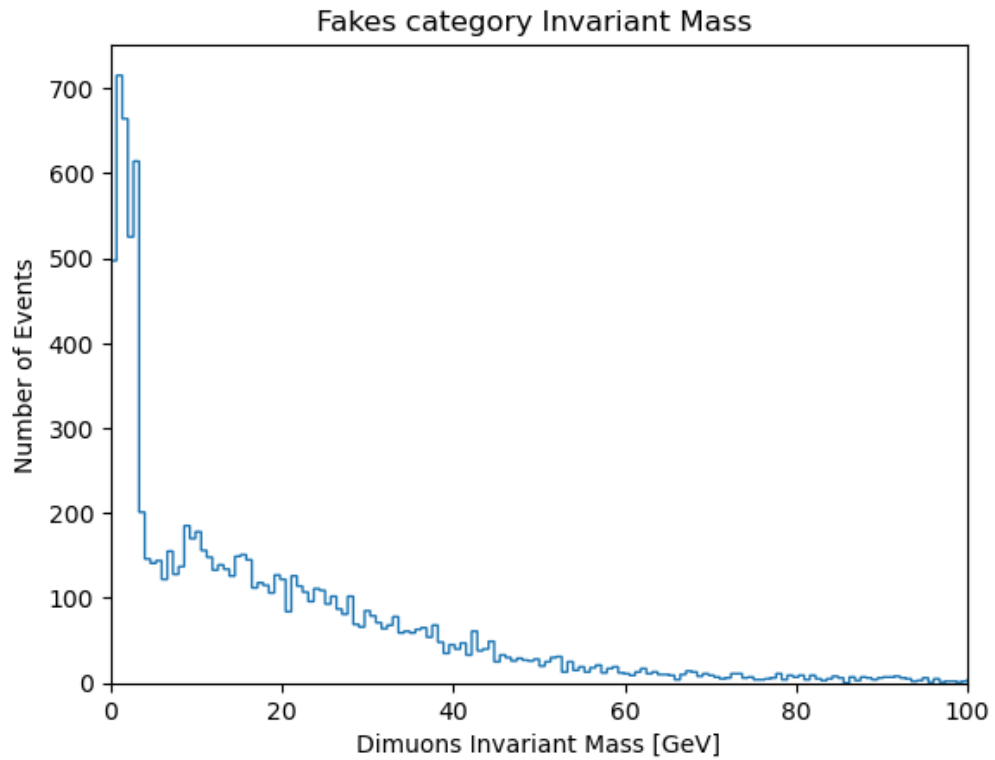


Fig 7: Dimuon invariant mass of the respective predictions

Conclusions

- Promising results were obtained for both DHJW and DTW scenarios with accuracies greater than 80 % in both cases
- ResNet50 has demonstrated to be the best CNN model among all the other popular options
- The DTW model could differentiate the Z boson resonance from a collection of real collision data

Muchas
gracias! /
Thank you very
much!

References

- [1] CERN — LHC images gallery. (2023, March 23). Disponible en : <https://home.cern/resources/image/accelerators/lhc-images-gallery>
- [2] Izaak Neutelings.
Cms coordinate system. disponible en: <https://tikz.net/axis3d cms/>
- [3] C. F. Madrazo, I. H. Cacha, L. L. Iglesias, and J. M. de Lucas, “Application of a convolutional neural network for image classification to the analysis of collisions in high energy physics,” CoRR, vol. abs/1708.07034, 2017.
- [4] “Ochoa, J. D. CNN-hep-thesis: Undergrad Thesis. using a CNN to classify different HEP processes. GitHub. Retrieved May 5, 2023, from <https://github.com/jose8af/cnn-hep-thesis>,”