IDENTIFYING HIGGS BOSON EVENTS IN √S =13 TeV ATLAS DATA USING DEEP NEURAL NETWORKS

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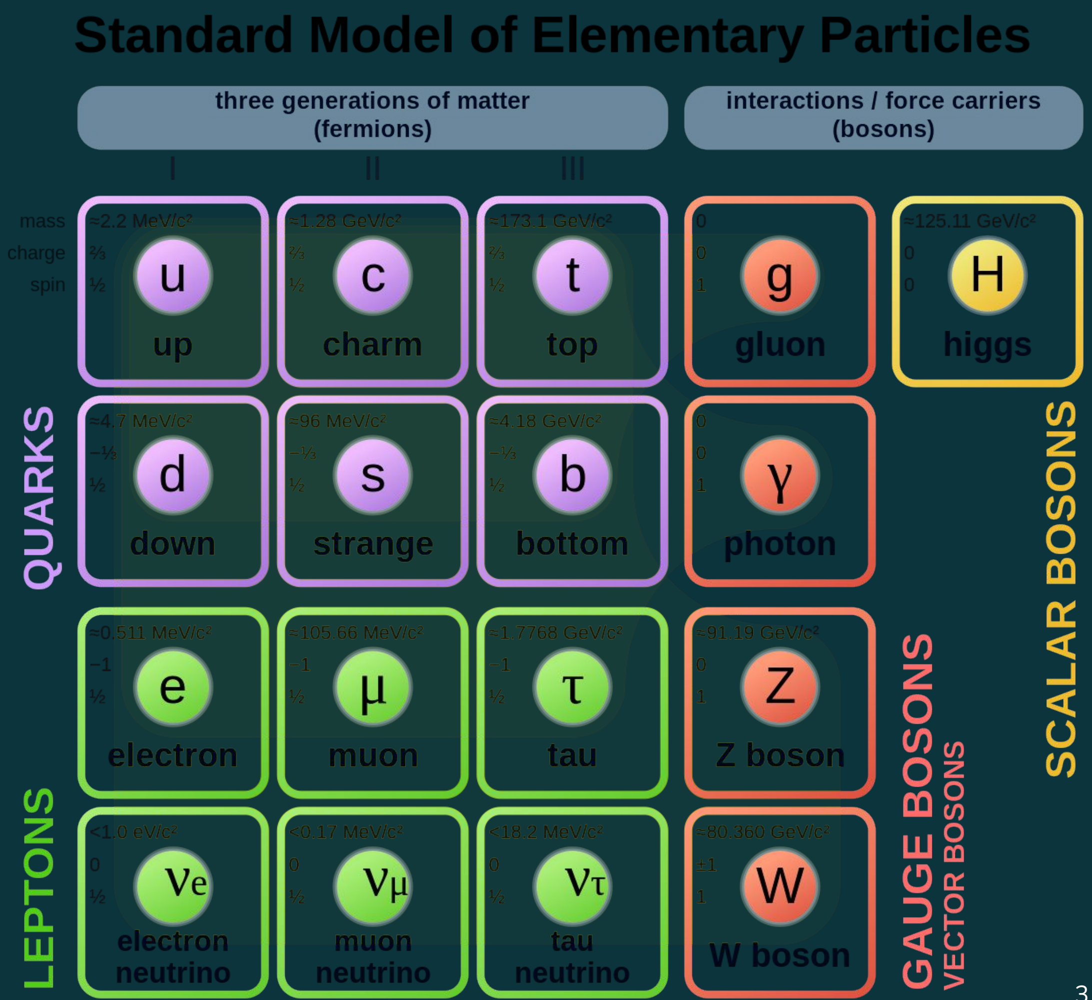
INTRODUCTION

- The Higgs boson is the fundamental particle associated with the **Higgs field**, an energy field that exists throughout the universe. Other elementary particles, like the W and Z bosons and quarks, acquire their **mass** through their interaction with this field
- It is the only particle in the Standard Model with **zero spin** (a scalar boson), making it unique. Its discovery at the LHC in 2012 was the final piece of the puzzle, triumphantly **confirming the Standard Model** of particle physics

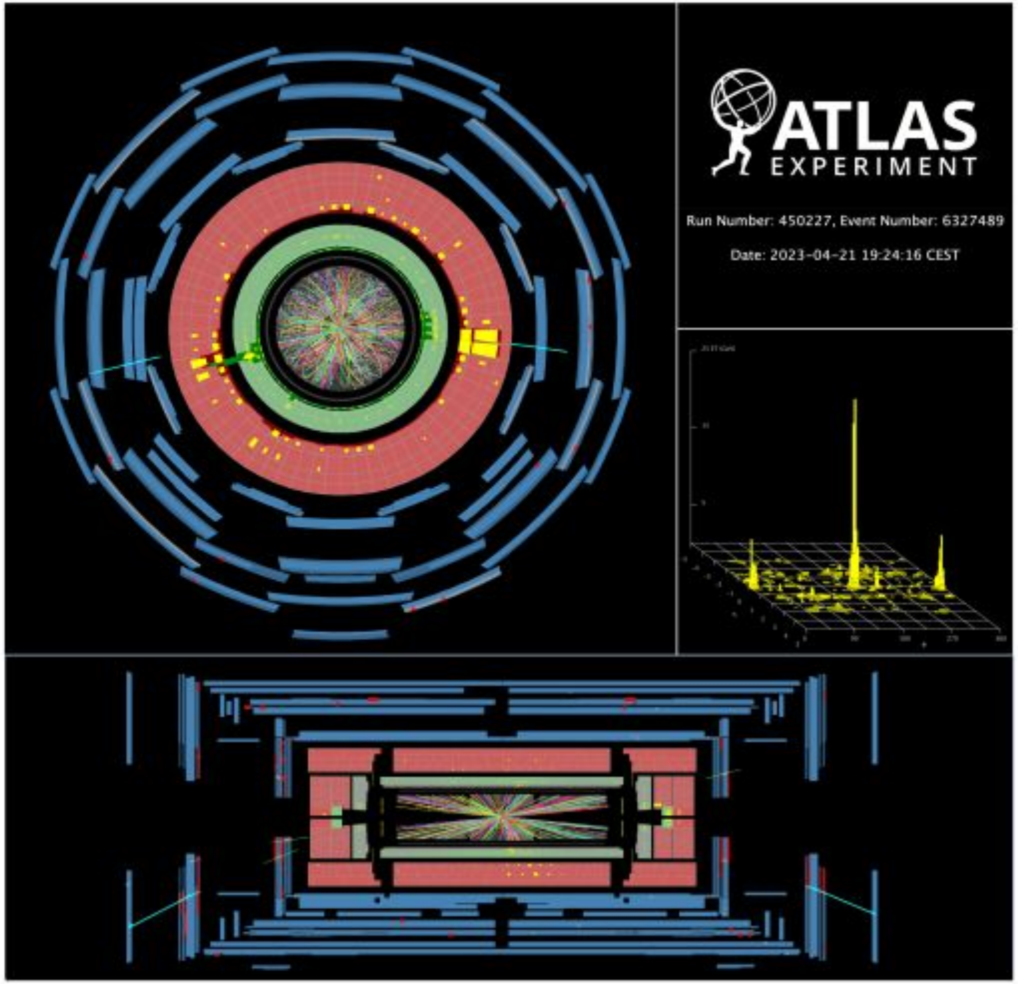


LITERATURE REVIEW

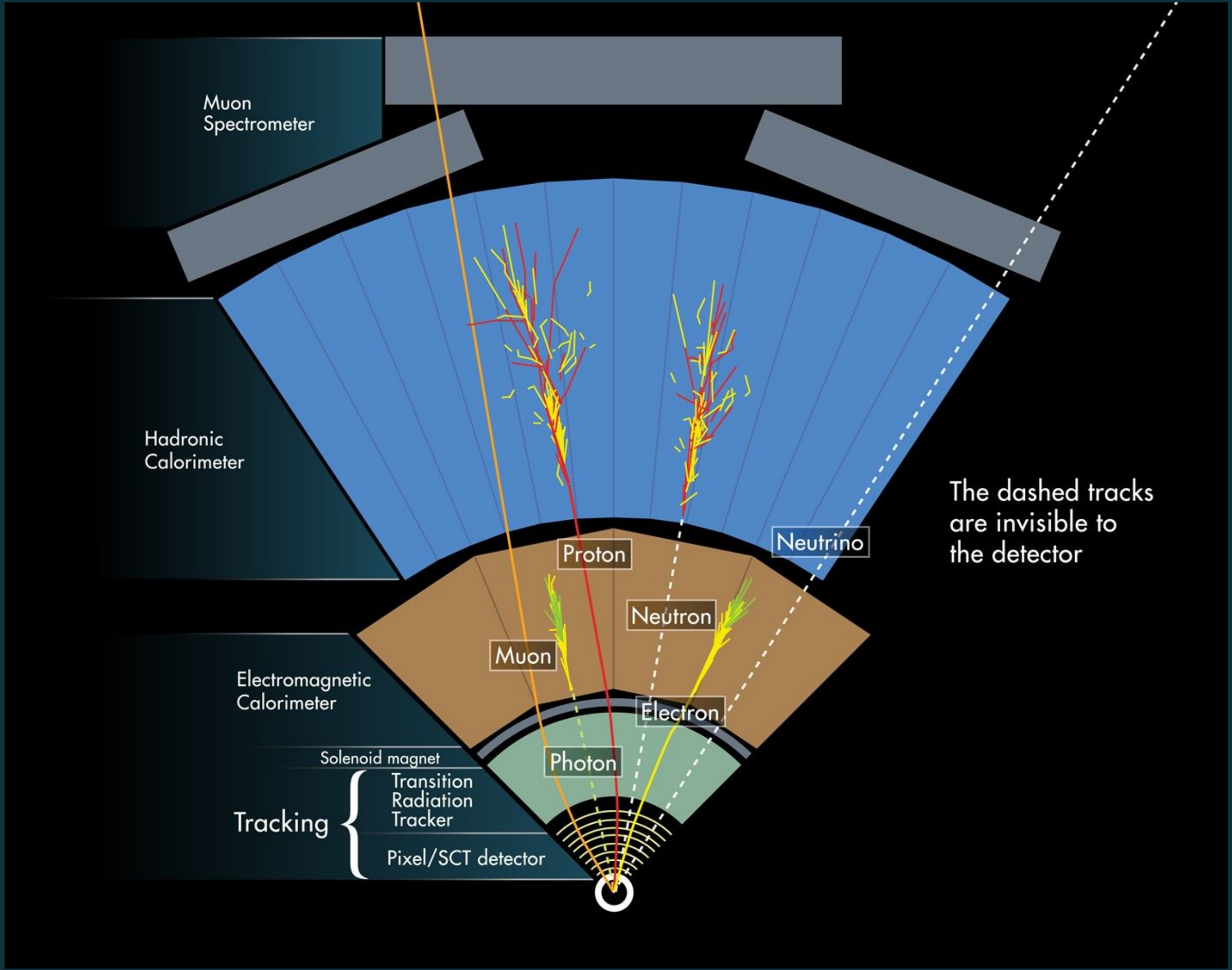

First Stable Beams
ATLAS
EXPERIMENT
proton-proton collisions at 13 TeV
Run: 266904
Event: 9393006
2015-06-03 10:40:31 CEST

TRANSVERSE VIEW

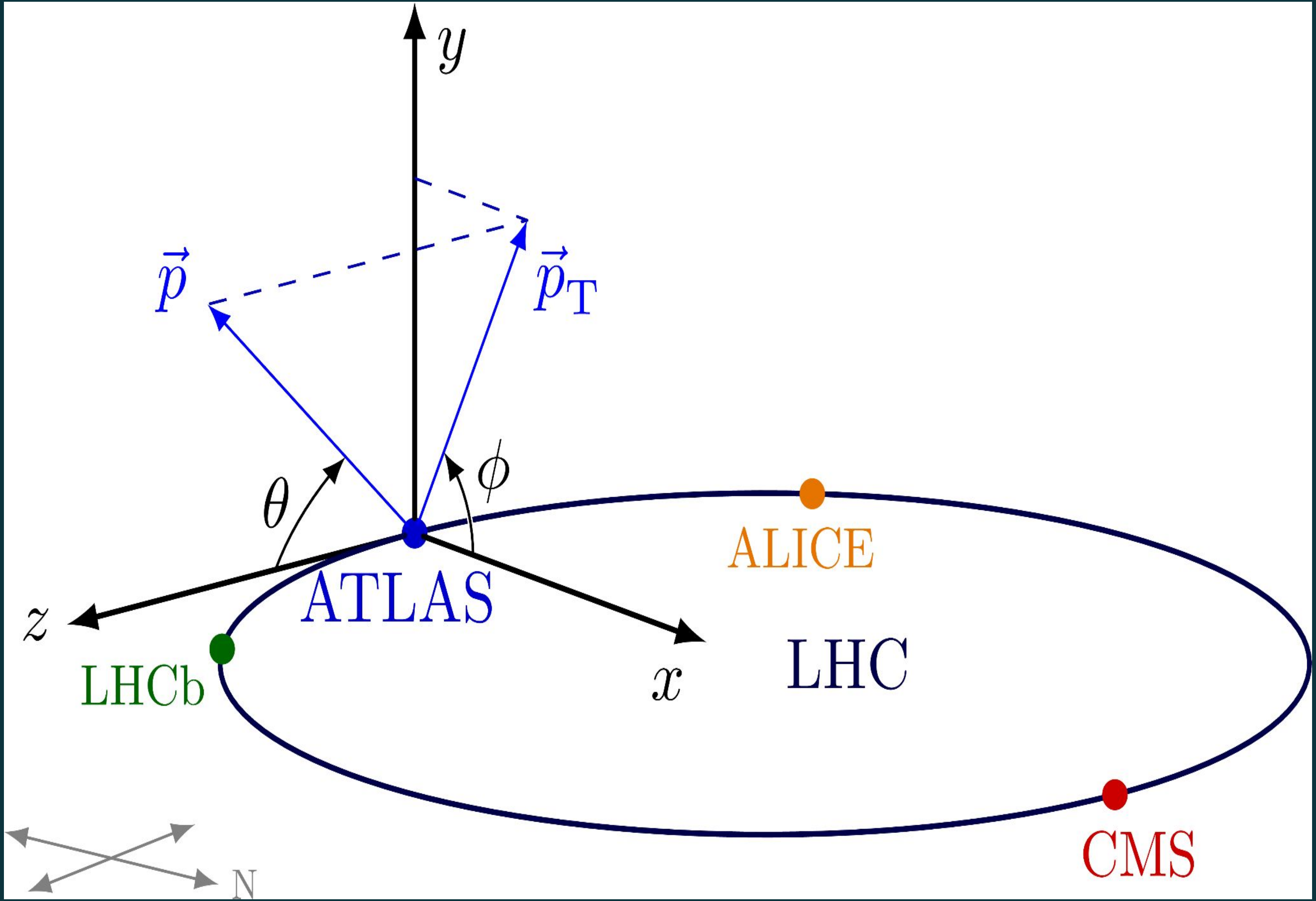
How do we see interactions



DETECTORS AND PARTICLES



ATLAS COORDINATE SYSTEM



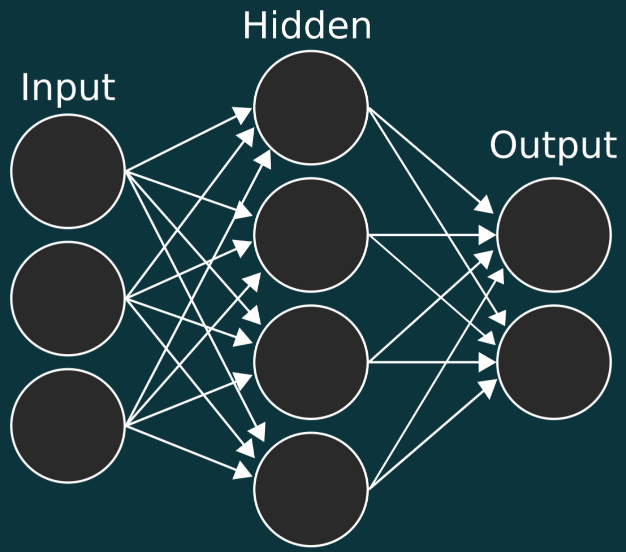
OBJECTIVE

- This project uses deep neural networks to identify Higgs boson events.
- The general objective is to classify Higgs boson events from proton-proton collision data.
- Specific objectives include developing a machine learning pipeline and evaluating model performance.
- The project involves preprocessing and extracting features from simulation files.
- Performance will be assessed using ROC curves, AUC scores, and statistical significance.

MATERIALS AND METHODS

Neural networks

Neural networks are a type of machine learning model inspired by the human brain. They consist of layers of interconnected neurons that process data by learning patterns from examples. Neural networks are especially powerful in HEP for tasks such as signal vs background classification, particle identification and event reconstruction.



Deep Neural Networks

- **Contain multiple hidden layers**
- Can learn complex, hierarchical features
- Require more data and computation, but achieve better performance on difficult tasks

Confusion matrix for binary classification

	True class: Positives (Signal)	True class: Negatives (Background)
Classified as: positives	**True Positives**	**False Positives**
Classified as: negatives	**False Negatives**	**True Negatives**

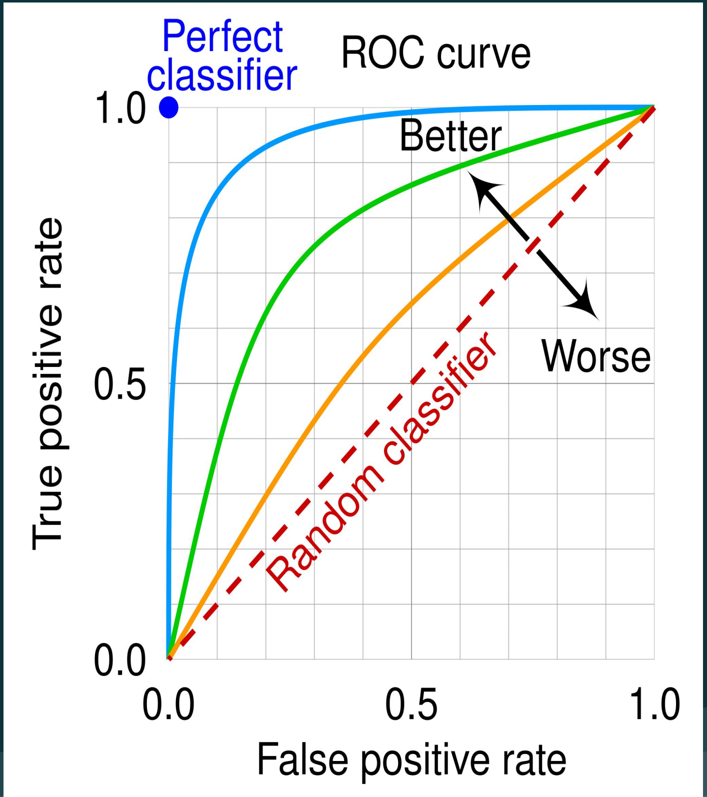
ROC curve and AUC

The ROC curve is a tool used to evaluate the performance of classification models. It plots the True Positive Rate against the False Positive Rate at various threshold settings.

- A model that perfectly separates classes will have a curve reaching the top-left corner.
- The Area Under the Curve (AUC) summarizes performance — the closer to 1 the better.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$



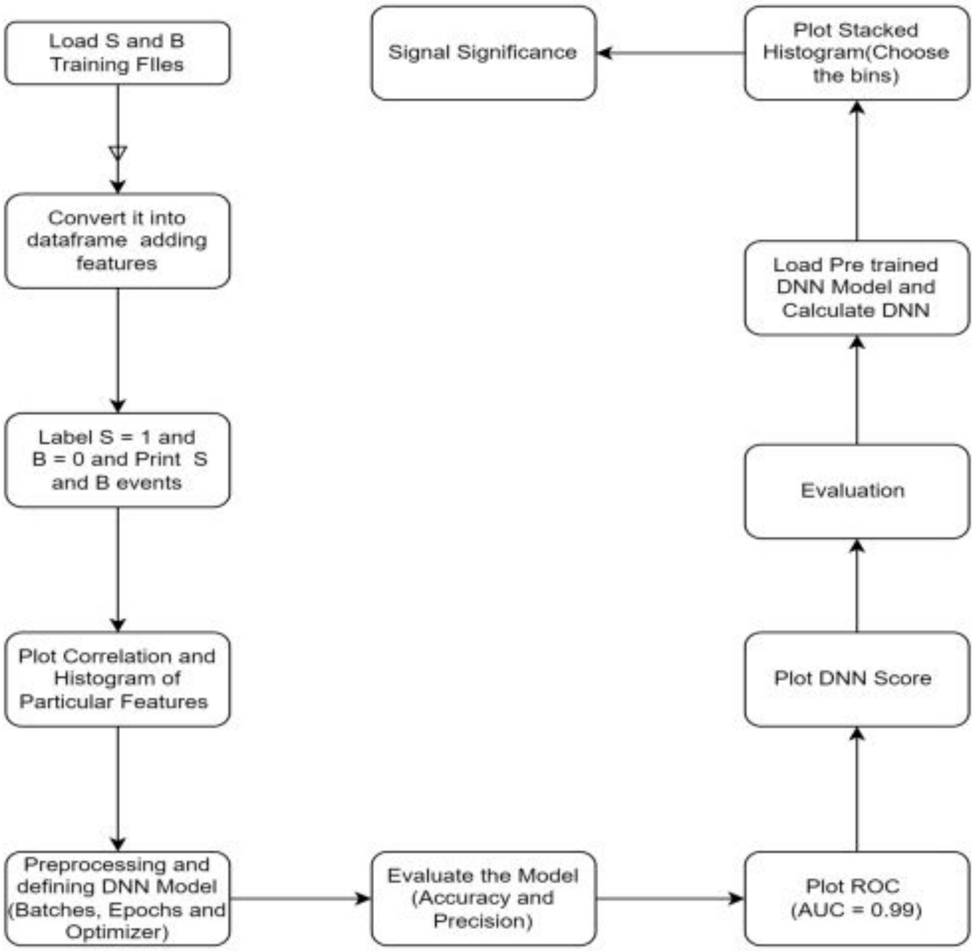
Signal significance

Signal significance measures how likely it is that an observed signal stands out above statistical background fluctuations. It helps quantify the confidence in detecting a real signal.

$$\sigma = \frac{TP}{\sqrt{TP + FP}}$$

PIPELINE FOR DNN MODEL

SCHEMATIC DIAGRAM



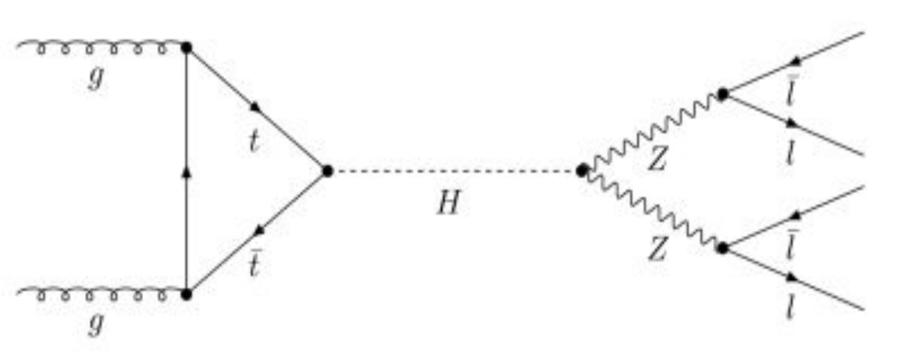
HOW DATA LOOKS LIKE IN HEP

]:

	lep_pt_0	lep_pt_1	lep_pt_2	deltaR_l0_l1	deltaR_l1_l2	lep_eta_0	lep_eta_1	lep_phi_0
0	47524.761719	36793.078125	20893.494141	2.877313	2.501741	-0.893228	-1.047406	0.188066
1	39326.449219	32071.375000	17291.861328	2.389075	1.075260	-0.989454	0.905732	-1.798553
2	69250.164062	30464.974609	13619.464844	2.899096	1.545332	-1.561571	-1.324680	0.612809
3	94496.953125	31211.234375	18642.890625	0.980899	0.548549	-0.914379	-1.075120	-2.015403
4	47351.773438	45956.453125	31686.111328	2.205387	0.855828	0.148054	0.824732	-0.326022
...	...	...	...	...	...	...	...	...
185015	47272.863281	32859.996094	32469.476562	0.509273	2.294434	0.389408	0.237044	-0.909866
185016	69816.351562	22364.453125	22344.648438	2.310738	1.242821	-1.327846	0.403557	2.899773
185017	49797.800781	43049.367188	32154.183594	1.476913	1.704283	-1.588342	-0.196426	-0.485490
185018	68900.726562	19986.732422	19552.453125	2.239844	2.090656	2.155998	0.230862	-1.634898
185019	34227.500000	31806.189453	20324.730469	2.818890	2.726076	0.342344	-0.804550	3.068871

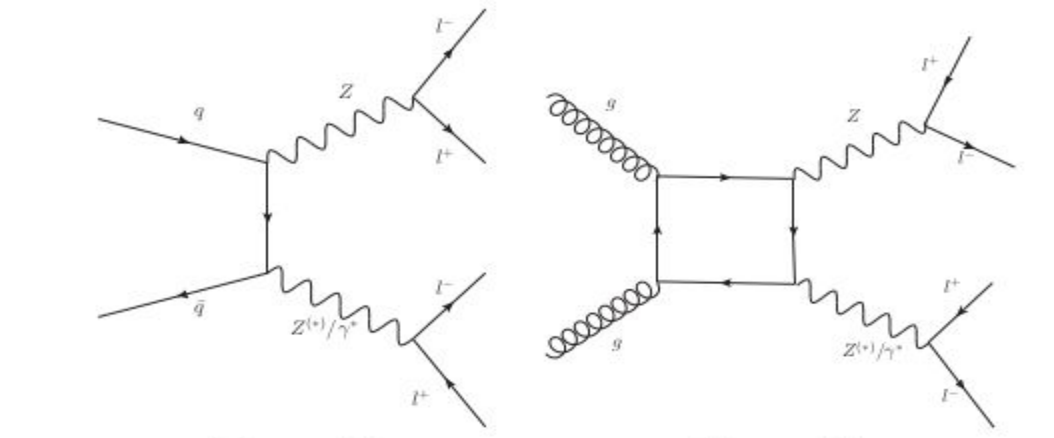
185020 rows × 8 columns

SIGNAL AND BACKGROUNDS



This Feynman diagram shows the main production mode for the Higgs boson at the LHC, called **gluon-gluon fusion**. The subsequent decay of the Higgs into two Z bosons, which then produce four leptons, is known as the "golden channel" due to its clean signature.

These diagrams illustrate the primary Standard Model **backgrounds** that mimic the Higgs signal. They show the direct production of a Z boson pair from either **quark-antiquark annihilation** (a) or **gluon fusion** (b), leading to the same four-lepton final state.

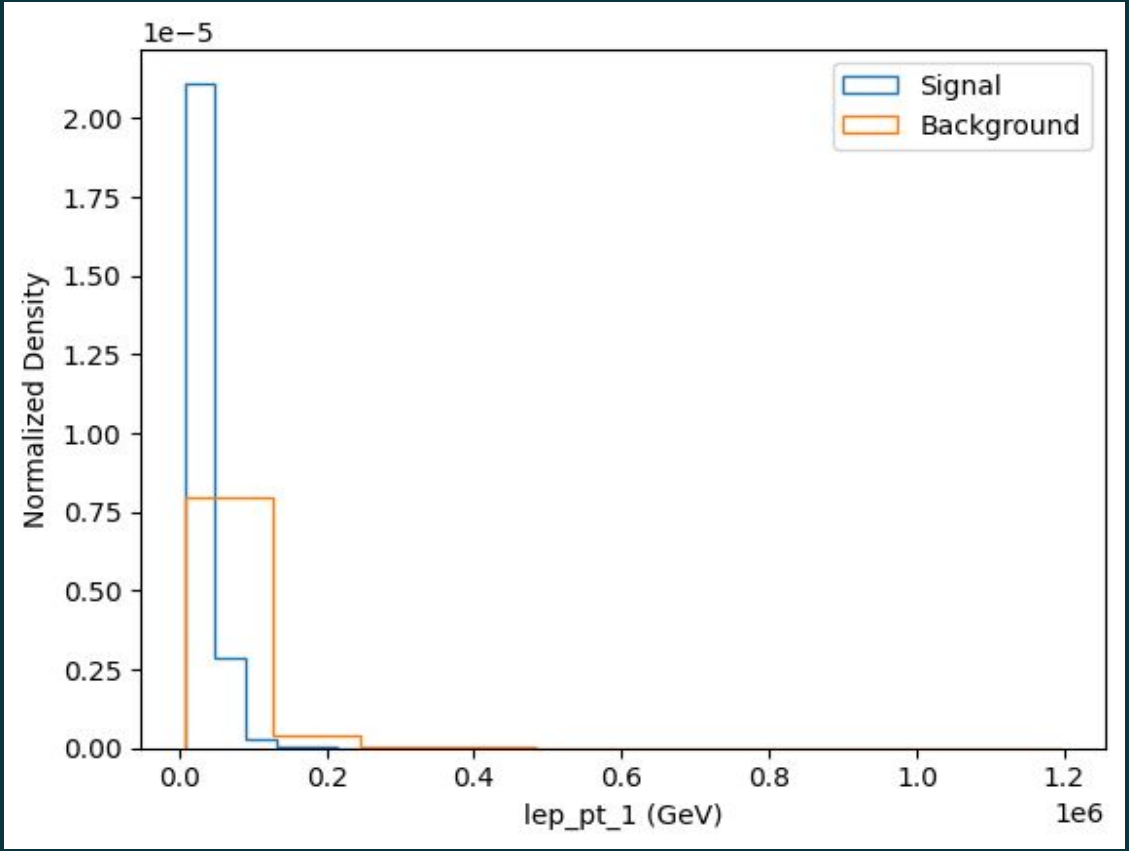


(a) $qq \rightarrow ZZ$

(b) $gg \rightarrow ZZ$

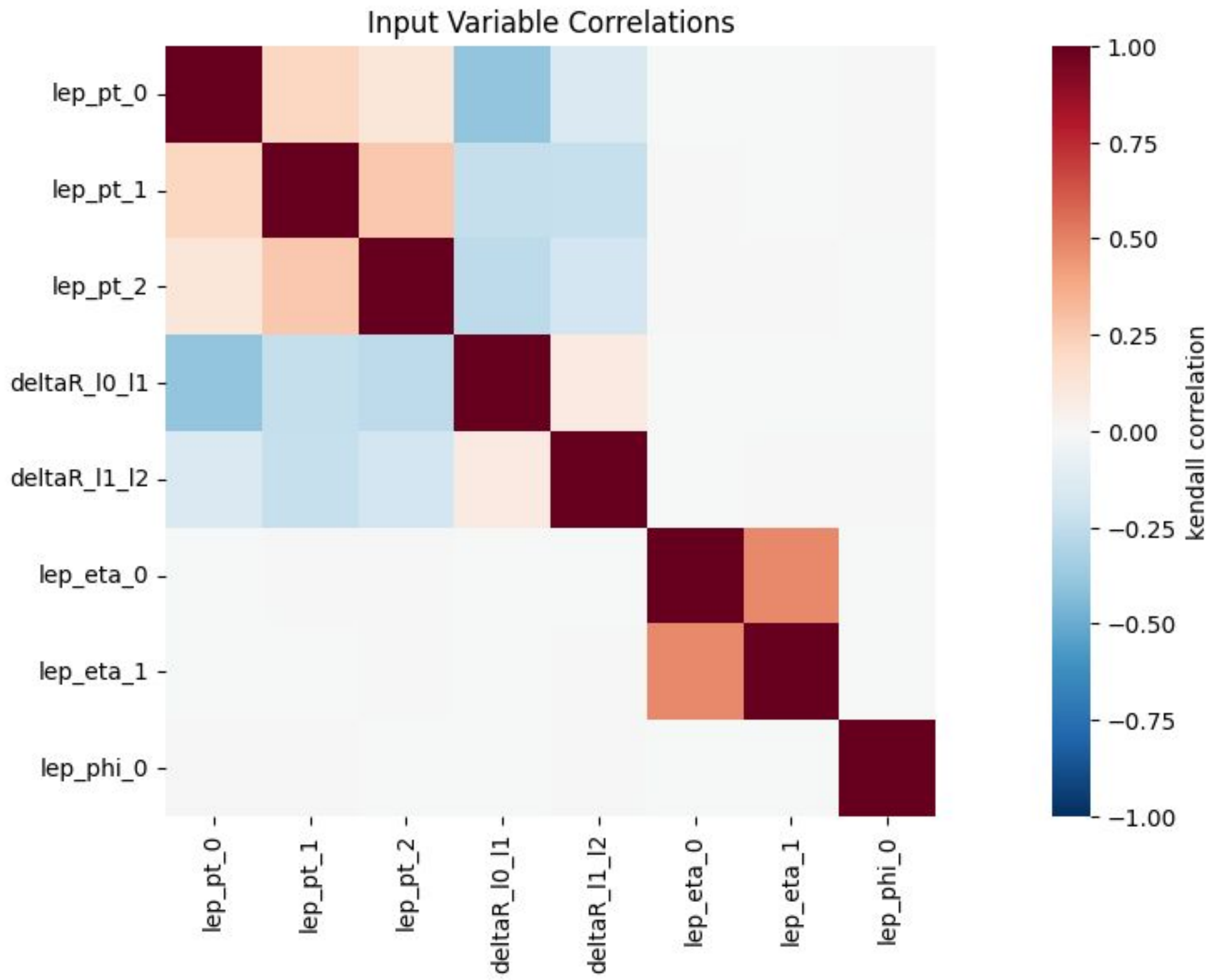
HISTOGRAM PLOT FOR FEATURES

This plot of the leading lepton's momentum (lep_pt_1) shows that the signal and background distributions almost completely overlap, indicating this feature alone does not provide a clear separation between the signal and background.



HEATMAP

A heatmap identifies correlated or uncorrelated features.



Some technical details

```python
#Define the neural network model
model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    layers.Dense(32, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])

#Compile the model
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy', 'Precision'])

#Train the model
history = model.fit(
    X_train_np, y_train_np,
    epochs=20,
    batch_size=32,
    validation_split=0.2, class_weight=class_weight_dict
)
```

Python

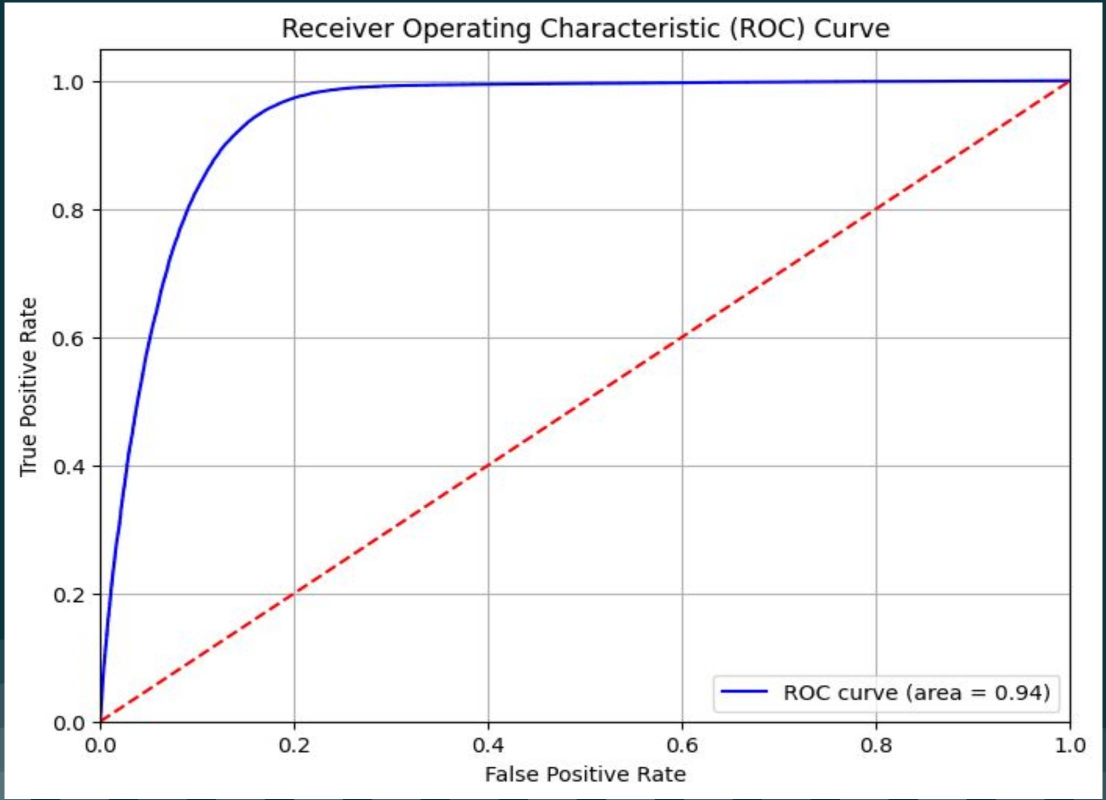
https://github.com/dippaakk/Higgs-Classification-using-ML

RESULTS AND DISCUSSIONS

AUC=0.94

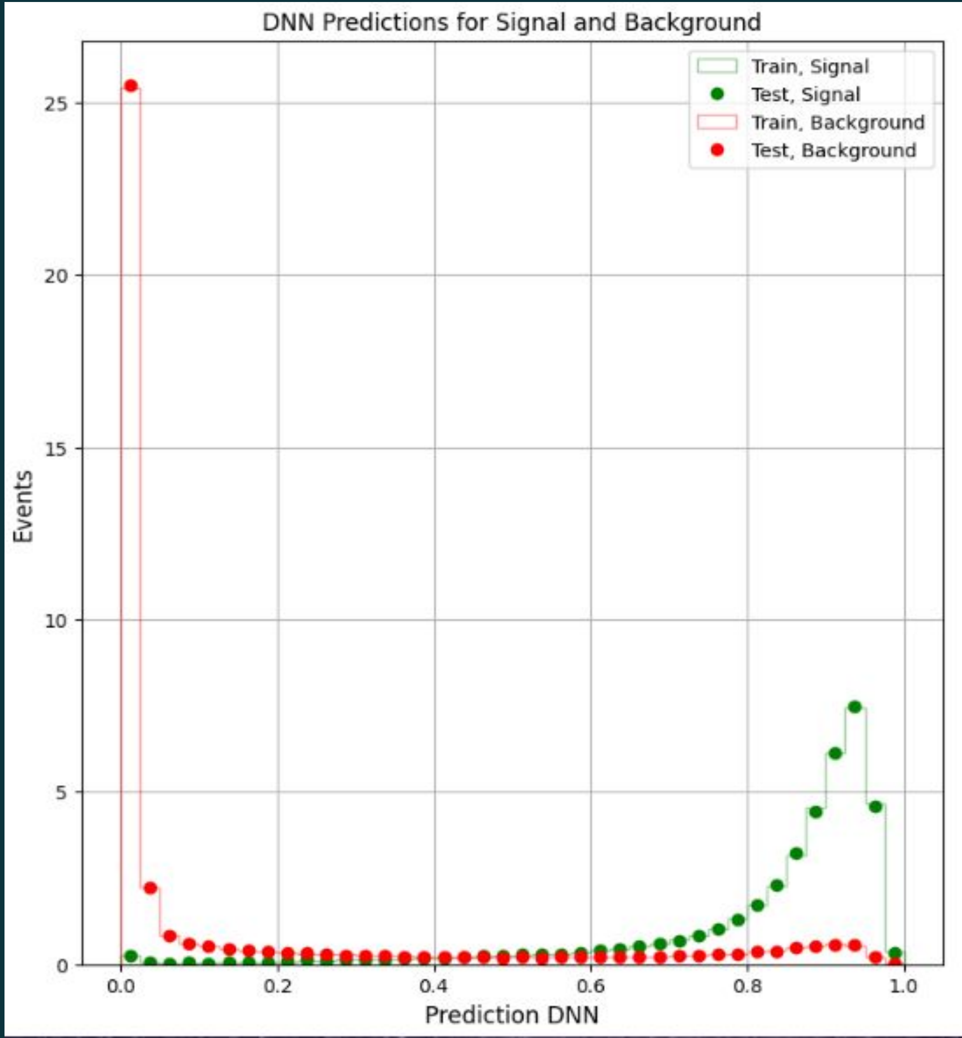
Accuracy: 0.8787829930101765

Precision: 0.7705386228747378

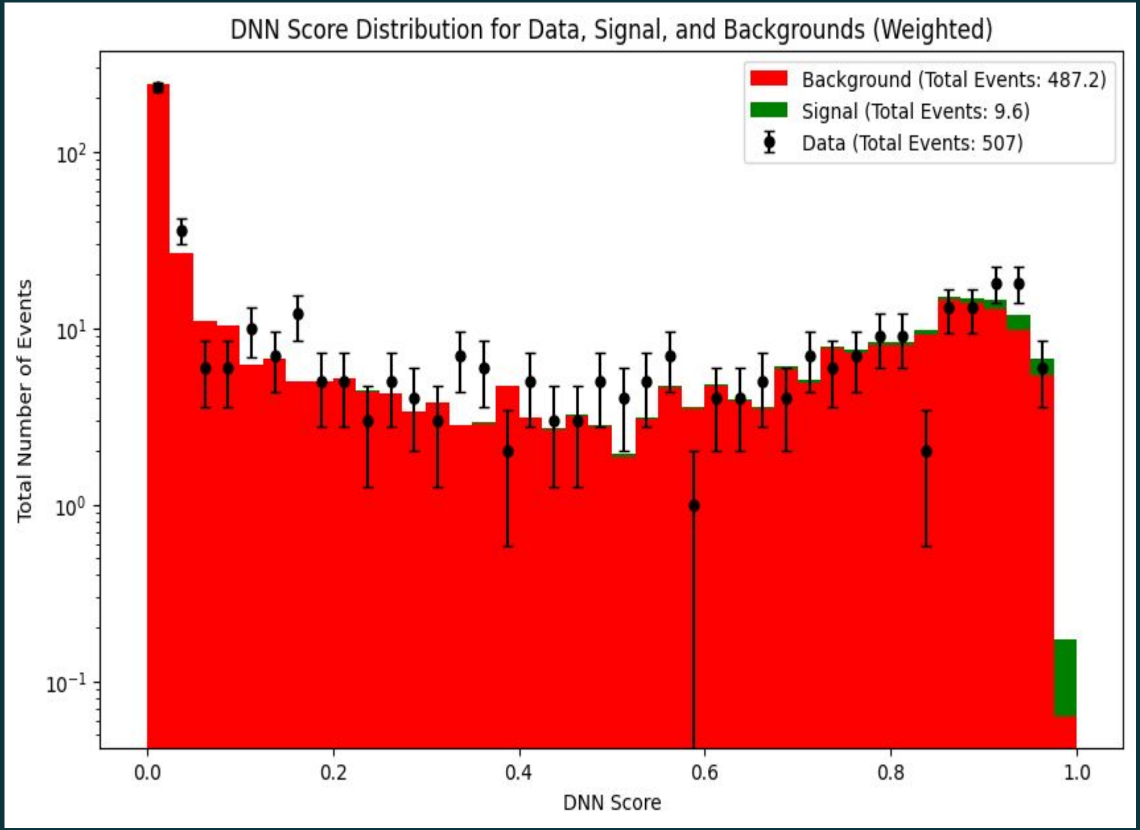


DNN SCORE

This plot shows our DNN classifier's high performance, as it effectively separates signal events (scores near 1) from background events (scores near 0). Furthermore, the excellent agreement between training and testing data confirms the model generalizes well and is not overfit.



Significance of Results



- Last two bins (DNN score from approximately 0.95 to 1.0):
– Signal (S): 1.366 events
– Background (B): 0.063 events
– Significance (Z_{sig}): 5.372 σ

CONCLUSIONS

- A DNN model effectively classified Higgs boson events from background processes.
- The model achieved a strong discriminative power with an AUC of 0.94.
- DNN scores clearly separated signal and background events.
- A 5.372 sigma significance was obtained, exceeding discovery thresholds.
- Machine learning tools show strong potential for particle physics discrimination.

Recommendations of future Works

- Explore advanced DNN architectures like CNNs and GNNs.
- Expand the feature space to include more physics-motivated variables.
- Implement systematic hyper parameter tuning for optimal configurations.
- Develop robust methods for quantifying statistical and systematic uncertainties.
- Extend analysis to multiple Higgs boson decay channels.

Acknowledgement

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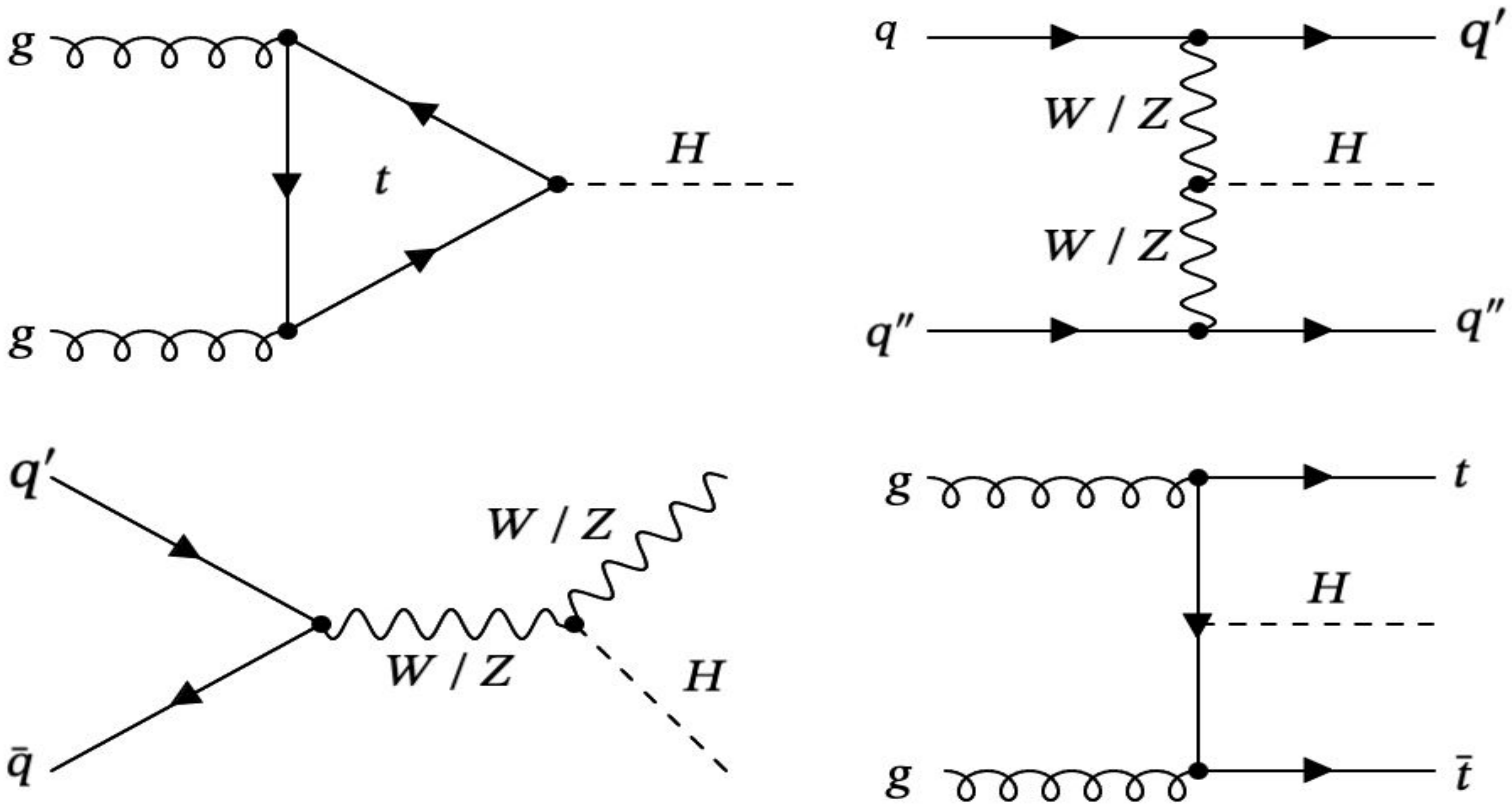
THANK YOU FOR YOUR TIME.

QUESTIONS?

BACKUP SLIDE


g
g
t
H
q
q′
W / Z
H
W / Z
q″
q″
q′
W / Z
W / Z
H
q̄
g
t
H
g
t̄

FEATURES

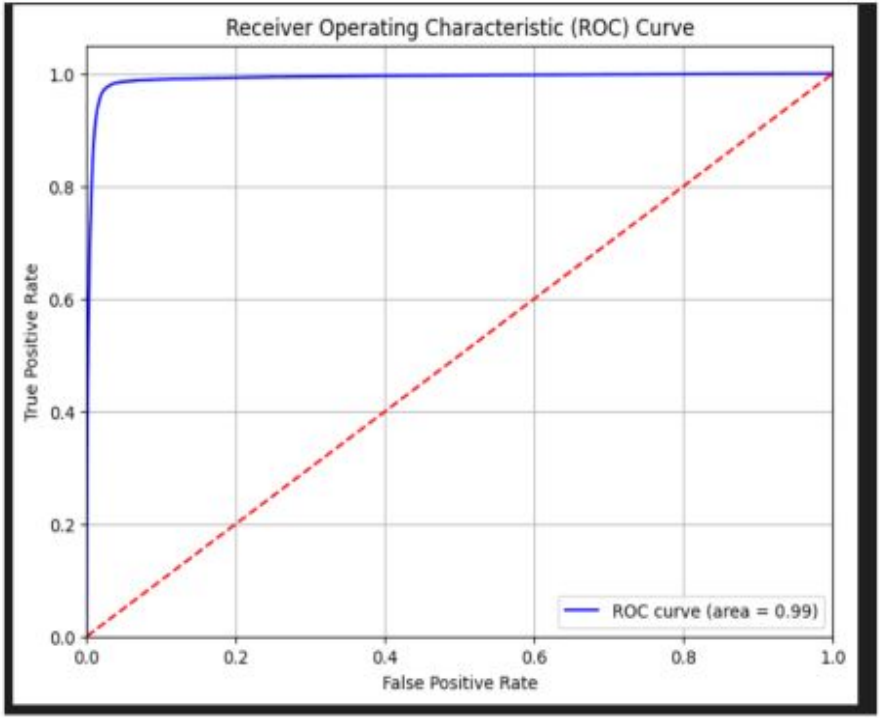
Total Signal events: 370040

Total Bkg events: 684349

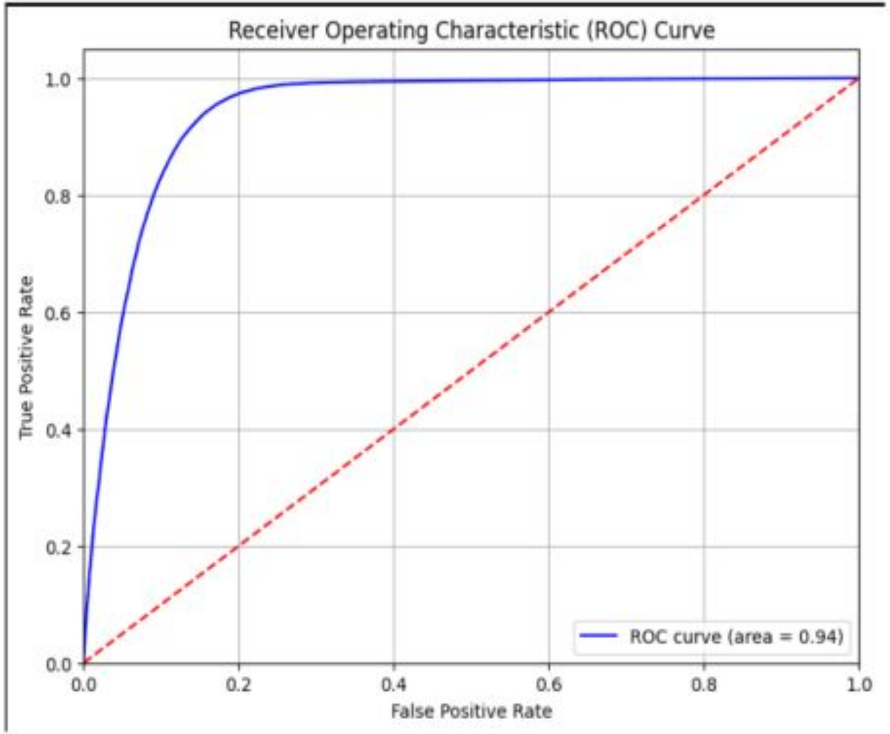
Total Data events: 507

```
: ['index',
  'lep_pt_0',
  'lep_pt_1',
  'lep_pt_2',
  'lep_pt_3',
  'invariant_mass_4lep',
  'deltaR_l0_l1',
  'deltaR_l0_l2',
  'deltaR_l0_l3',
  'deltaR_l1_l2',
  'deltaR_l1_l3',
  'deltaR_l2_l3',
  'totalWeight',
  'lep_eta_0',
  'lep_eta_1',
  'lep_eta_2',
  'lep_eta_3',
  'lep_phi_0',
  'lep_phi_1',
  'lep_phi_2',
  'lep_phi_3',
  'lep_E_0',
  'lep_E_1',
  'lep_E_2',
  'lep_E_3',
  'lep_n',
  'jet_n']
```

ROC CURVE

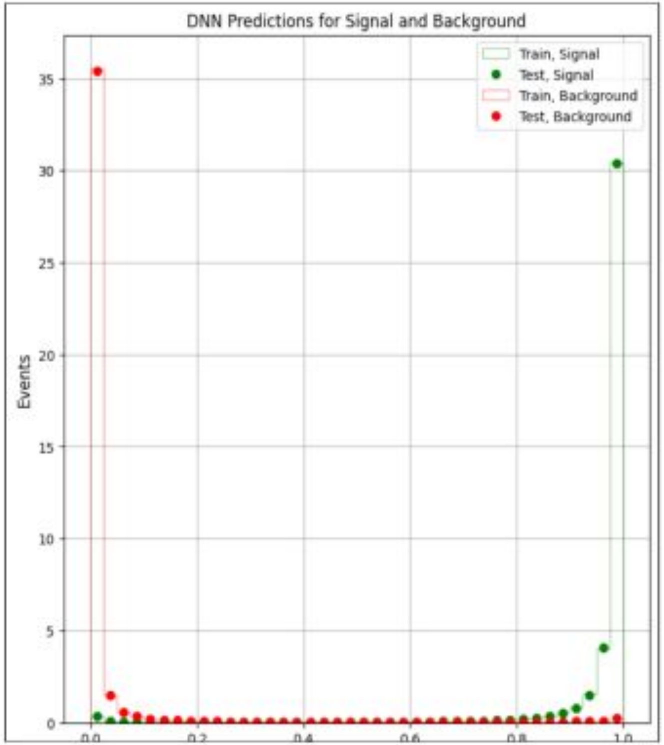


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.99)

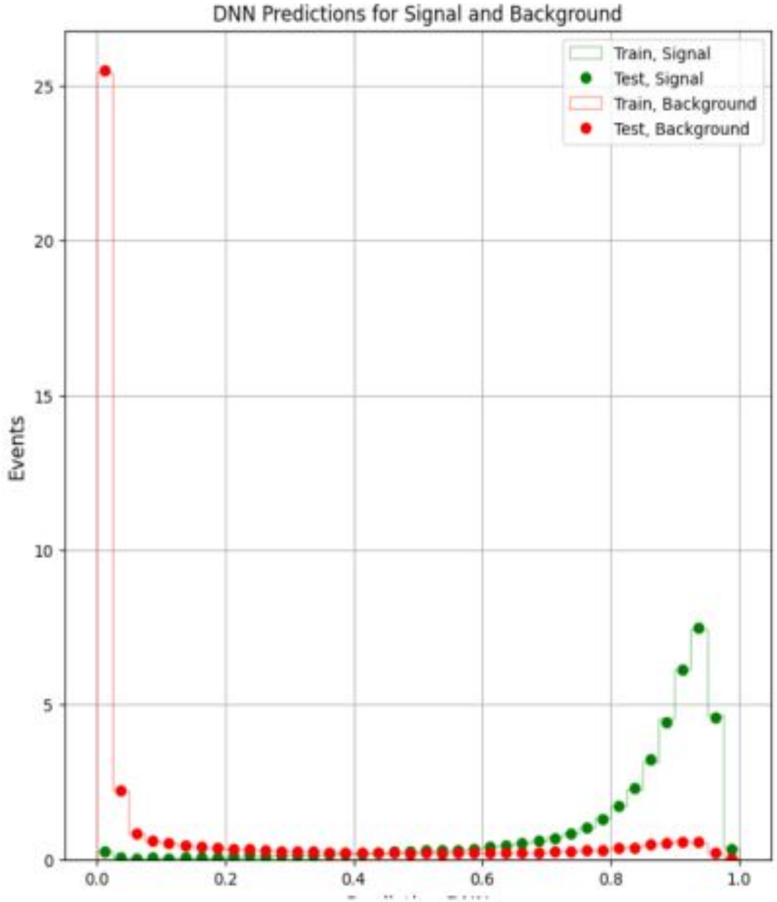


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 0.94)

DNN SCORE



Accuracy: 0.9743…………
Precision: 0.9538…..



Accuracy: 0.8787829930101765
Precision: 0.7705386228747378