

Background and Objectives

The CP symmetry of the Higgs Boson has its first ever model independent measurement in July 2020 by the CMS Collaboration. The CP mixing angle is found to be $4 \pm 17^\circ$ [1], which is consistent with the Standard Model prediction of a CP mixing angle of 0° .

CP sensitive variables known as acoplanarity angles can be constructed [2], however, to further constrain the current measurement, we aim to use deep learning techniques on 'low-level' particle decay data. We focused on a binary classification problem – classifying Higgs as either CP-even or CP-odd. The project focuses on the $H \rightarrow \tau\tau$ decay, particularly on $\rho - \rho$, $\rho - a_1$, $a_1 - a_1$ (3pr) decay channel

Our project aims to:

- Develop a novel data pipeline to extract and calculate additional features
- Optimise machine learning architecture for the CP Higgs problem
- Reconstruct CP sensitive information from neutrinos
- Develop a machine learning algorithm to be able to discriminate against CP-even/CP-odd Higgs

Results

Key results:

1. Able to **produce discrimination** against CP states with deep learning (Table 1.).
2. **Neural network** consistently outperforms XGBoost.
3. Problem is **heavily architecture reliant**.
4. **Reconstructed neutrinos** can provide some discrimination.

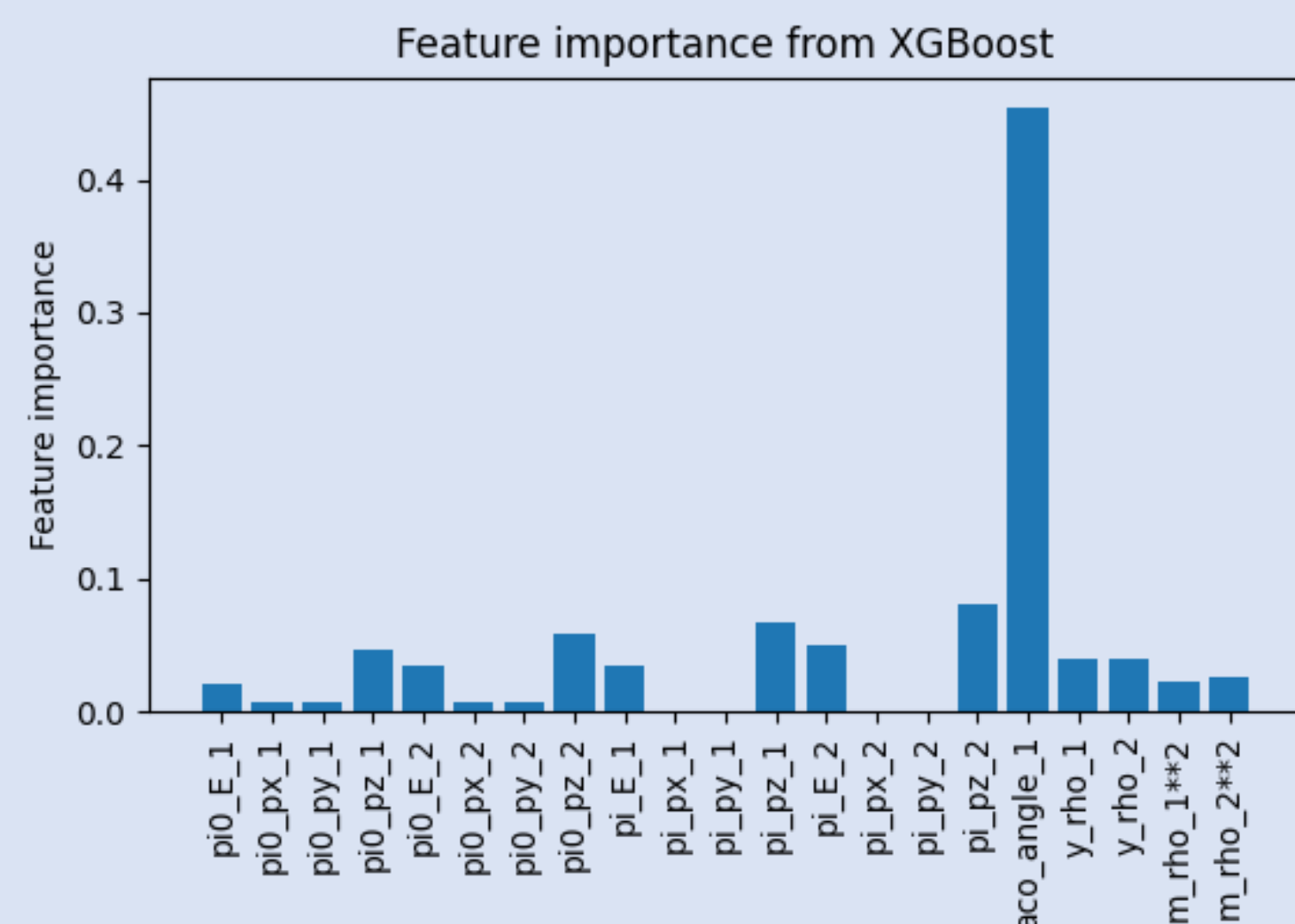


Fig. 3. Importance of features obtained from XGBoost model. The acoplanarity angle is by far the most important feature, but other features do give more information

Decay channel	AUC score (higher = better)	
	Gen level (3.s.f)	Reco level (3.s.f)
$\rho - \rho$	0.679	0.596
$\rho - a_1$	0.633	0.570
$a_1 - a_1(3pr)$	0.576	0.542

Fig. 2. Example of neural network architecture after tuning. This architecture includes 3 densely connected hidden layers

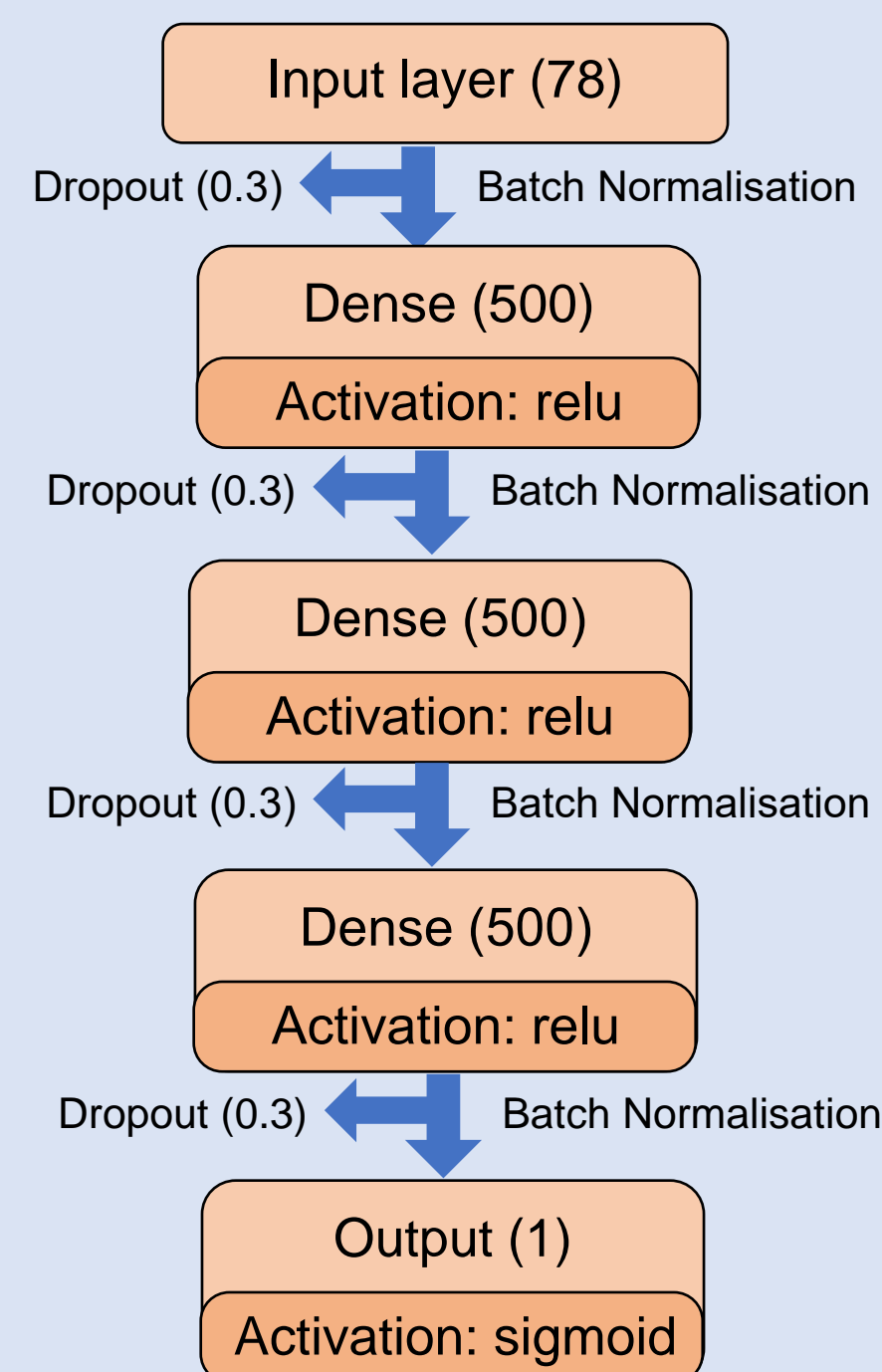
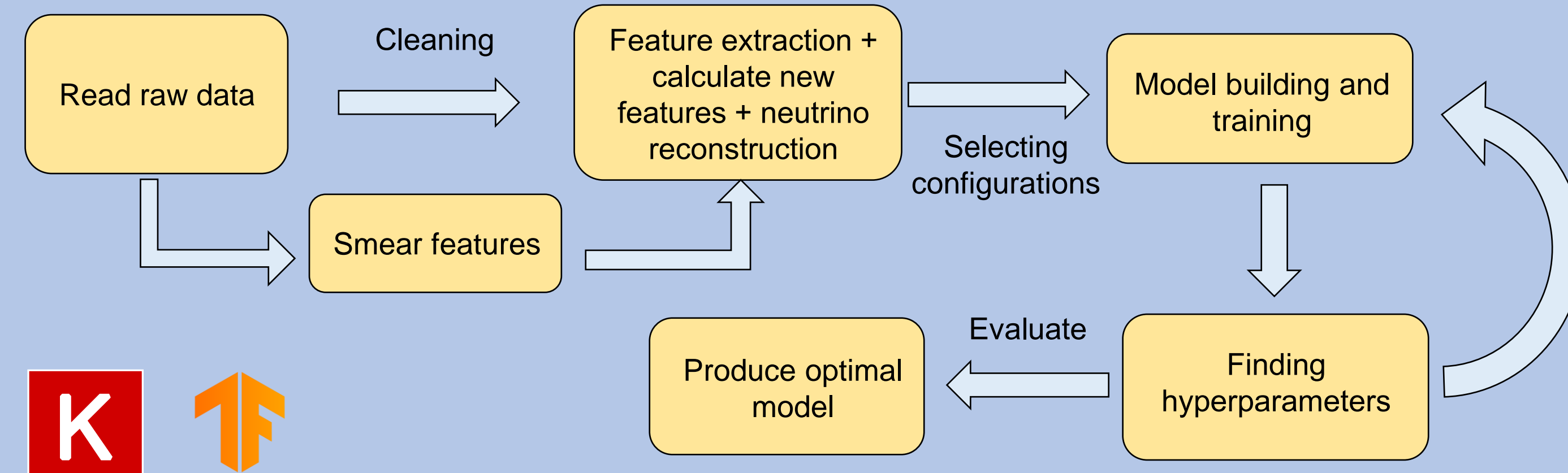


Table 1. Our best AUC scores from the neural net. AUC stands for area under the curve, which is an important performance metric of binary classification.

Our Work

Novel data pipeline



The data pipeline is built in Tensorflow and Keras. The two main machine learning techniques used are neural networks and XGBoost [3].

Calculating additional features

We construct acoplanarity angles between all combinations of intermediate decay products, which all have some degree of CP sensitivity. An example of the sensitivity of an acoplanarity angle is given in Fig 1.

Reconstructing neutrinos

Using additional detector information, we improved current methods of reconstructing neutrinos by adding the polarimetric vector method and other mass constraints. This information is then fed into the pipeline.

Investigating optimal ML architecture

There are many hyperparameters in our model, e.g., the number of neurons in each layer, the number of layers, the learning rate, and so on for a neural network. For optimising these, we used the hyperopt package.

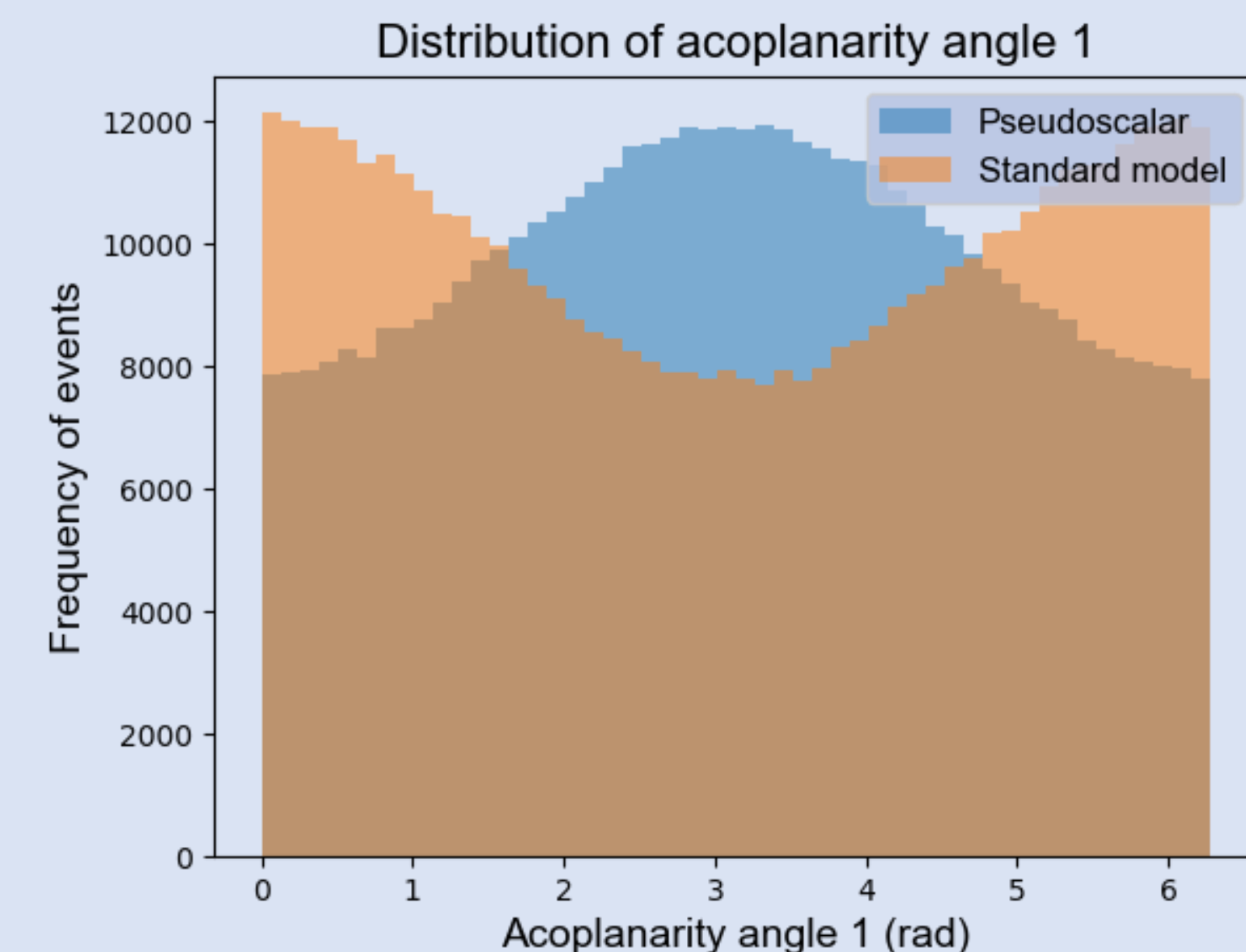


Fig. 1. Distribution of acoplanarity angle 1. This variable is highly CP sensitive, which means we have a difference in the pseudoscalar and standard model distributions.

Conclusions

We found that deep learning techniques, particularly neural networks are able discriminate against CP-even and CP-odd Higgs Bosons.

We have developed a novel data pipeline able to extract and calculate new features for this problem. Neutrino reconstruction was able to add some CP sensitivity in the algorithm, however we found that performance was highly dependent on network architecture

The next stage of the project is to identify which smeared features are most important to the analysis.