`LIP-STUDENTS-22-28`

Identification of kaons using Neural Networks in COMPASS and AMBER experiments at CERN

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October 14, 2022

Abstract. A study on the impact of certain problems on the ability of Neural Networks to identify kaons at the CEDAR detector at CERN. The Network was trained with data generated by Monte Carlo simulations and its performance is studied in order to understand the influence of each configuration of problems (used in the simulation). The results for various configurations are presented and the best ones are discussed. The results are consistent and may provide sufficient information for what changes need to be made to improve the identification of kaons.

KEYWORDS: kaons, Neural Networks, CEDAR

1 Introduction

1.1 The CEDAR detector

The differential Cherenkov counter, CEDAR, is one of the detectors used in the AMBER and COMPASS experiments at CERN and is used to detect kaons. The detector consists of a cylindrical chamber filled with gas at a controlled pressure. It is equiped with 8 photodetectors known as PMTs that are placed around it. When a beam of particles passes through the detector it emits a ring of photons as cherenkov radiation that has a certain radius, depending on the particle that makes up that beam. The photodetectors are placed so that they all should fire when a beam of kaons passes through. Since other particles emit bigger and smaller rings, no PMT should be activated.

1.2 The Problems

In recent years the beam intensity for these experiments was increased. However, the detector was not updated to deal with this, which means that under current conditions, it is not able to effectively identify kaons. The problems caused by this increase can be separated into 4 categories: correlated noise, that happens when there is an additional non detected track; random noise and inefficiency; angle smearing. This last one is a particular complex problem because the high intensity beam is not properly collimated due to limited length of the beam line. Moreover, the beam angle at CEDAR is not know precisely because, due to the high intensity beam, precise Silicon detectors cannot be used for the beam angle measurement.

Due to these problems, a pure kaon beam can activate any number of PMTs and a beam made up of other particles can also activate PMTs unlike it should. So, the main goal of this study was to understand how each of these problems affects the identification of kaons and what updates are required to make it viable.

Each configuration of problems is labeled like this:

- xxxx → configuration
- 1xxx → correlated noise
- x1xx → random noise
- xx1x → inefficiency
- xxx1 → angle smearing

(They can also be represented as x_x_x_x)

For example, 4_13_25_20 config means that it has 4% correlated noise, 1.3% random noise, 2.5% inefficiency and $20\mu rad$ smearing.

1.3 The Method

As mentioned earlier, under current conditions a kaon beam can activate any number of PMTs. Thus, in order to distinguish these particles from others, there was used a Neural Network which had as input the angle of the beam and how many and which PMTs fired for a given beam. The Network was trained with data from Monte Carlo simulations and it's performance on how well it identified kaons was studied. The network classifies an event as kaon if the output for kaon is above a given threshold which was set. The neural network was optimized and was composed of 4 layers: one 11 neurons input layer; two hidden layers (50 and 25 neurons respectively) and an output layer with 2 neurons. It was used the swish activation function and during the optimization process it was concluded that the results were not dependent upon the size of the network (number of layers and neurons).

All events were separated into signal events which are kaons and background events which are pions and protons. Afterwards we can check which events the network selected as signals and as background. With this information we can calculate the efficiency and the background reduction factor, that are given by,

$$Efficiency = \frac{\#selected\ signal\ events}{\#signal\ events}$$

$$BG\ reduction = \frac{\#BG\ events}{\#selected\ BG\ events}$$

These values are crucial to evaluate the performance of the Network.

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1.4 Starting Point

The first step was to use Monte Carlo simulations in which inefficiency and random noise were considered as only one problem (x1x) and all three problems were binary: they either were present as in reality or they were totally removed.
By doing the plot of the BG reduction factor against the efficiency (ROC curves), it is visible that, if we solve all problems, the network's performance is almost perfect which is far from the current situation (Figure 1).

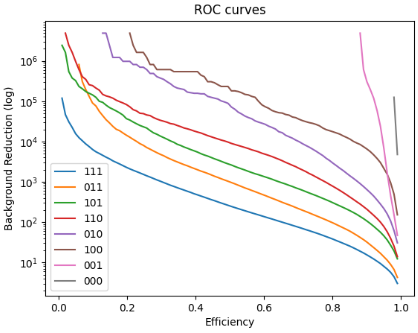


Figure 1. ROC curves for the starting point configurations.

This starting point is useful to get an overall idea on how each problem affects the performance of the network. It can be seen that if we remove all problems except for the angle smearing, the network becomes very efficient at distinguishing kaons from the rest which could indicate that this problem would be the least important. However, if only one problem is solved, it is visible that the angle smearing has the most influence. Therefore, it is possible to understand that these problems are not so linear and might be correlated.

1.5 Further analysis

In order to get a deeper understanding of the problem, there were used Monte Carlo simulations with different configurations for the four problems in which they could also be partially solved, not only fully removed. Therefore, instead of only ones and zeros, the problems can have various values between zero and their real value.

To make the detector viable, it is required a BG reduction factor of around 1000 for 80/90% efficiency. At current conditions there is a reduction factor of 38 at 80% efficiency, which is very far from the goal. As it was done at the starting point, ROC curves were used to get an overall idea on the problems (Figure 8).

Having the curves for all configurations plotted makes it possible to see that most of them are far below the required threshold. This means that they are not viable solutions. Despite this, there are some curves that meet up the required values and so the best of them were plotted (Figure 2).

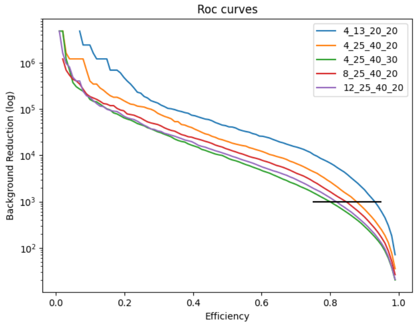


Figure 2. ROC for the best configurations found.

In order to further analyze these results, the data was organized in tables which makes it possible to more accurately compare the values (see attachments). Solution 4_13_20_20 (Figure 3) is the best, since there is even a 1000 BG reduction factor at 90% efficiency. However, it implies reducing all problems to very low values. By looking at all configurations it is visible that they all require reducing angle smearing by at least 50% . Configuration 4_25_40_30 (Fiure 5) allows for a slightly higher smearing than the rest. It is also possible to only reduce correlated noise by 25% (Figure 7).

There were also analyzed Monte Carlo simulations in which there was always a second non detected track (Figure 9). Above 80% efficiency we can see that no curve reaches the 1000 reduction factor and that most don't even reach the 100 factor. This shows that under such conditions, the network cannot properly identify kaons.

1.6 Future work

Even though these results seem to provide sufficient information, there is more to do, mainly by improving the performance of the network. As so, the next step would be to take advantage of the fact that each PMT is composed of 4 pads and use the input of each of these pads as the input of the network, which means that we would be using a 35 neuron input layer instead of only 11.

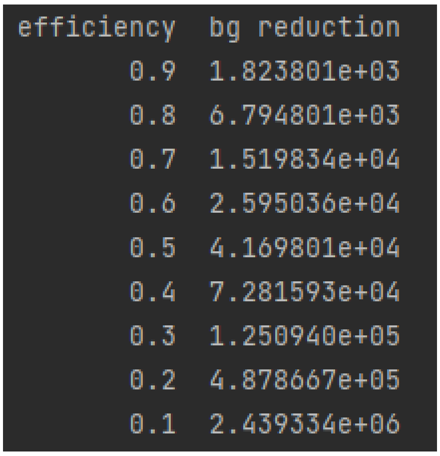
2 Results and Conclusions

With the data obtained, it can be concluded that in order to make the detector viable for identifying kaons, there needs to be a great investment on upgrading its components, since the data shows that small changes will not suffice. Moreover, it shows that from all problems, angle smearing is the one that must be significantly reduced. It can also be concluded that if there is always a non detected second track, the network is not able do identify kaons.

Acknowledgements

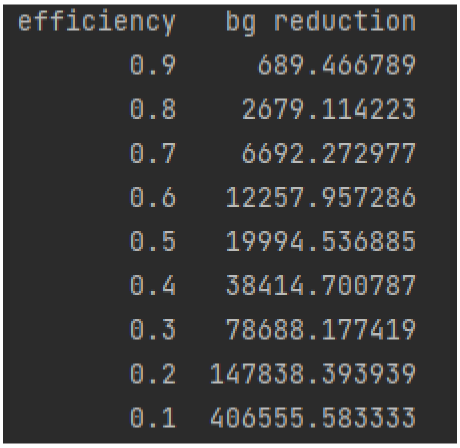
I want to thank my supervisor, Marcin, for all the support and patience to teach me the basics for this project.

3 Attachments



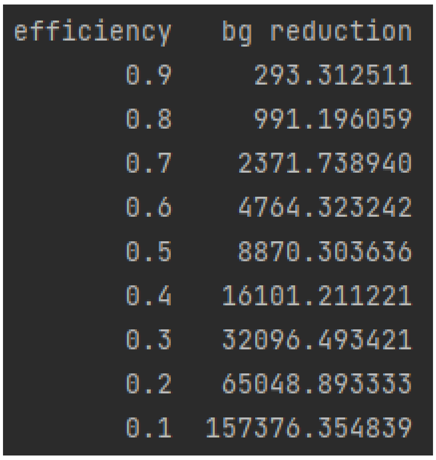
```
efficiency  bg reduction
       0.9  1.823801e+03
       0.8  6.794801e+03
       0.7  1.519834e+04
       0.6  2.595036e+04
       0.5  4.169801e+04
       0.4  7.281593e+04
       0.3  1.250940e+05
       0.2  4.878667e+05
       0.1  2.439334e+06
```

Figure 3. Table for 4_13_20_20 configuration.



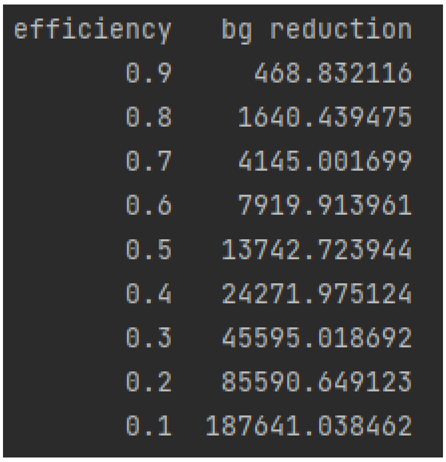
```
efficiency   bg reduction
       0.9     689.466789
       0.8    2679.114223
       0.7    6692.272977
       0.6   12257.957286
       0.5   19994.536885
       0.4   38414.700787
       0.3   78688.177419
       0.2  147838.393939
       0.1  406555.583333
```

Figure 4. Table for 4_25_40_20 configuration.



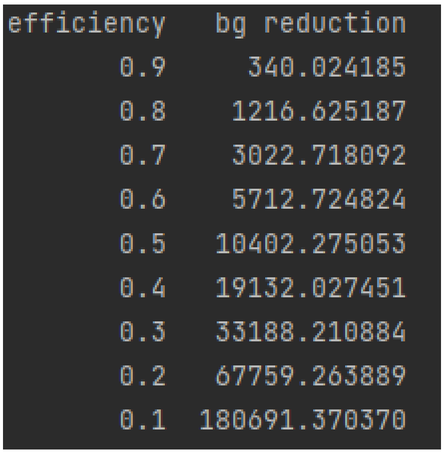
```
efficiency   bg reduction
       0.9     293.312511
       0.8     991.196059
       0.7    2371.738940
       0.6    4764.323242
       0.5    8870.303636
       0.4   16101.211221
       0.3   32096.493421
       0.2   65048.893333
       0.1  157376.354839
```

Figure 5. Table for 4_25_40_30 configuration.



```
efficiency   bg reduction
       0.9     468.832116
       0.8    1640.439475
       0.7    4145.001699
       0.6    7919.913961
       0.5   13742.723944
       0.4   24271.975124
       0.3   45595.018692
       0.2   85590.649123
       0.1  187641.038462
```

Figure 6. Table for 8_25_40_20 configuration.



```
efficiency   bg reduction
       0.9     340.024185
       0.8    1216.625187
       0.7    3022.718092
       0.6    5712.724824
       0.5   10402.275053
       0.4   19132.027451
       0.3   33188.210884
       0.2   67759.263889
       0.1  180691.370370
```

Figure 7. Table for 12_25_40_20 configuration.

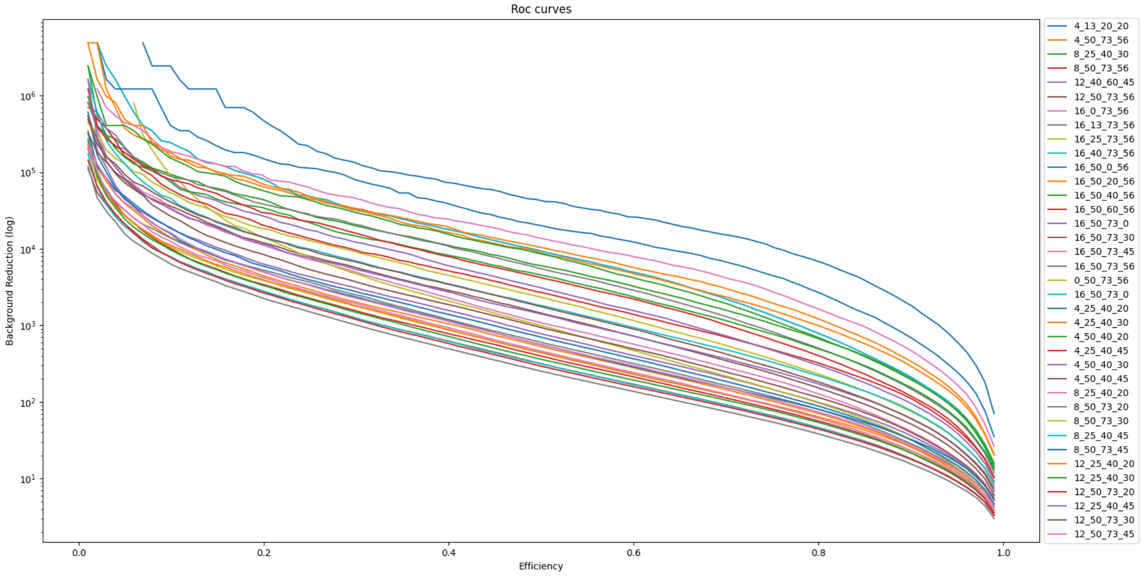


Figure 8. ROC curves for all configurations

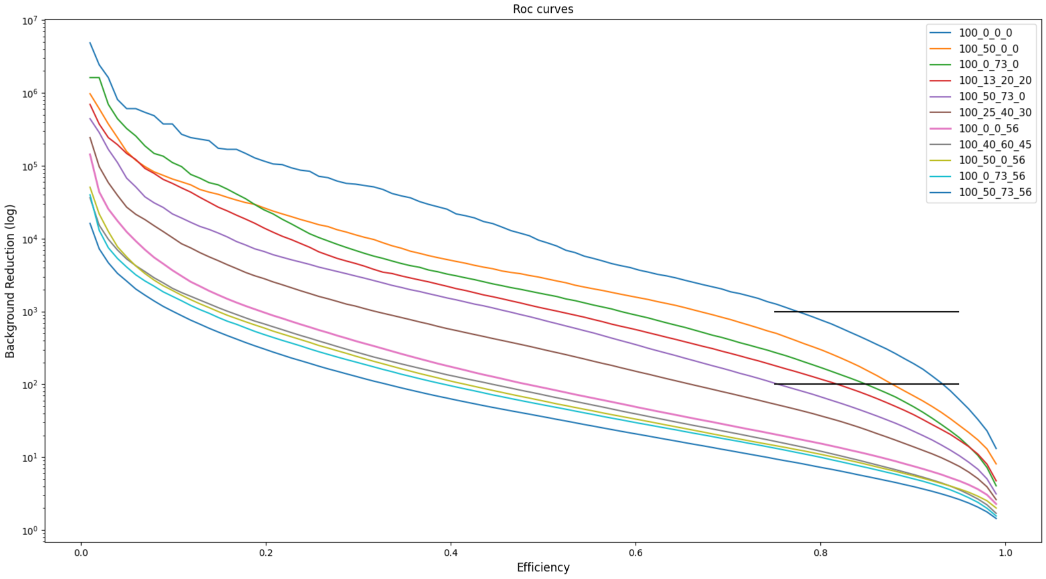


Figure 9. ROC curves for configurations where there is always a second non detected track.