Horizontal muon track identification with neural networks in HAWC

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Introduction

The HAWC observatory consists of a large 22,000 m^2 area densely covered with 300 water Cherenkov detectors [1]. Nowadays there is an alternative line of research that proposes to use this observatory as an indirect neutrino detector [2, 3]. This idea is based on the Earth-skimming technique, here we want to get an interaction between a neutrino and a nucleon that form Pico de Orizaba mountain.

Motivation

Figure 1 shows a visual comparison between a horizontal track and an air shower. As can be seen, each of these events has a characteristic shape that visually makes it easy to distinguish. we propose an analysis with a convolutional neural network (CNN) to replace the last step to the algorithm mention in [3]. In this work we test three different models: two based on image classification (model A and B) and one on object detection. For model A we use the normal image given by the official HAWC display (Fig. 1 a) and for model B we remove the tanks and photomultipliers (PMT's) that were not activated (Fig. 1 b).

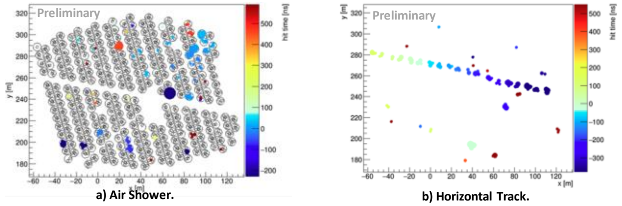

Figure 1. Visual comparison between a horizontal track and an air shower.

CNN: Image classification

Network architecture: For model A and B, we used the convolutional network VGG16 [4].
Training data: We used 1050 tracks images and 5627 air shower images.
Validation dataset: We used 116 tracks images and 116 air shower images. This set is used to calculate the loss function and the success rate in each of the training steps (Figure 2)..

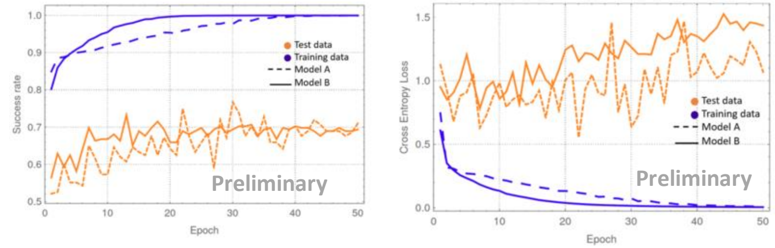

Figure 2. Loss and success rate for both models A and B.

Test dataset: We used 100 tracks images and 1000 air shower images. Whit this set, In figure 3 we show a precision (proportion of positives identifications that was correct) vs recall (proportion of all positive identifications that was correct) for different threshold values. The threshold value is the number from which we consider that an event is positive or negative. An event classified as a track was taken as positive and an event classified as an air shower was negative.

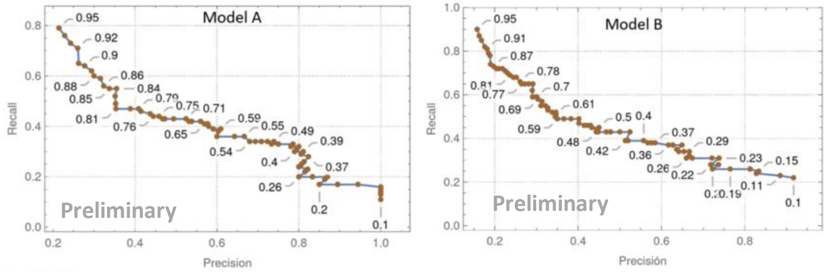

Figure 2. Precision vs recall for both models.

CNN: Object detection

Network architecture: The model used was the faster_rcnn_resnet101_coco. This is a pre-trained model, and it is found within the models for API object detection [5].
Dataset: For training data, we used 2866 tracks images and 2860 air shower images. For test data, we use the same images as in the previous network (model A), just the second dataset.
In figure 4 we show an example of a track and air shower identified in an event. Also, in figure 5 we show the loss function for this type of network.

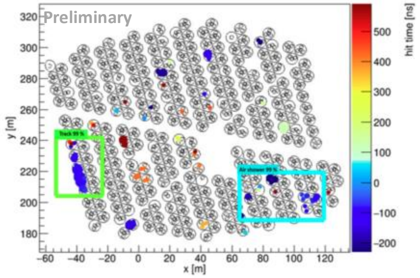

Figure 4. Output image for the CNN focused on object detection.

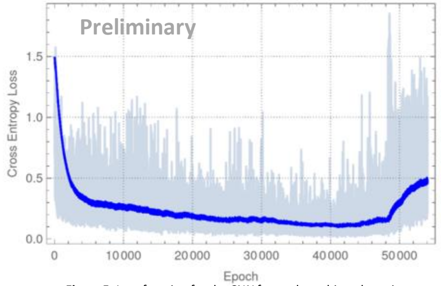

Figure 5. Loss function for the CNN focused on object detection.

Model Comparison

After analyzing the test dataset, in table 1, we show the threshold value or reliability percentage for which we obtained the highest value for precision variable.

Model	Threshold	%		
		Precision	Recall	False positives
A	0.1	100	11	0
B	0.1	91	22	0.2
Object detection	99 %	100	11	0

Table 1: Threshold value with greater precision for the three models.

Using these threshold values, We analyze a real dataset consists of 118476 candidates. Then we identify horizontal tracks in these events using our neural networks, the results are shown in table 2. This table also shows the number of tracks identified by the step that we replace (Filtering of candidate tracks) in [3].

Model	Tracks identified	False positives
A	103	3
B	125	5
Object detection	92	0
Filtering of candidate tracks	9	0

Table 2: Comparison of tracks identified by all models for the same set of real data.

Conclusion

All our neural networks had an increase of an order of magnitude in the number of tracks identified, compared to the previous algorithm. Also, model B had the highest number of tracks identified, so in this case using a clearer image improves the detection process, but it had the highest number of false positives. However, the object detection network did not have false positives. The results of this study could be used in the future to improve the performance of the Earth-skimming technique for the indirect measurement of neutrinos with HAWC.

References:

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[2] H. León Vargas, A. Sandoval, E. Belmont and R. Alfaro, Capability of the HAWC Gamma-Ray Observatory for the Indirect Detection of Ultrahigh-Energy Neutrinos, Advances in Astronomy (2017) 1932413 [arXiv:1610.04820].
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[4] Karen Simonyan and Andrew Zisserman Very Deep Convolutional Networks for LargeScale Image Recognition, The 3rd International Conference on Learning Representations (ICLR2015). [arXiv:1409.1556] 1
[5] J. J. Yebes, D. Montero and I. Arriola, "Learning to Automatically Catch Potholes in Worldwide Road Scene Images," in IEEE Intelligent Transportation Systems Magazine, doi: 10.1109/MITS.2019.2926370.