Neutrino Classification Through Deep Learning

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Abstract

Neutrinos are a type of sub-atomic particle whose study is expected to allow us to gain a better understanding of cosmic phenomena and the universe itself. The study of these particles begins with the detection of their passing through a Water Cherenkov detector and, once the data has been collected it is analyzed to determine properties such as its energy, direction of travel and its class. In this project we implemented 4 deep learning methods for the classification of neutrino events as one of three classes: gamma, electron and muon, with the objective of determining which algorithm works best, state of the art methods include custom Convolutional Neural Networks (CNNs) or deep learning algorithms, such as ResNet50 itself, but with other hyper-parameters. Our results show that among the implemented methods, ResNet 50 yielded the best results, with an accuracy of 72.48% and an Area Under the Curve for the efficiency plot of 0.71. These results were obtained by employing the largest dataset available which showed the importance of having a big enough representation of all types of events of all classes in the analysis.

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1 Introduction

Studying neutrinos is expected to provide significant insights into the universe's functioning since these highly elusive particles have specific qualities like not having charge and thus interacting minimally with matter along their path od travel directly from their origin up to a detector, or more importantly, presenting a behavior called oscillation, in which they can be measured to have a different flavor from the one they actually have [1,2].

Because neutrinos are difficult to observe, we need special detectors in which we can manage to catch information about their passing, these detectors work on the principle of catching the Cherenkov radiation produced when neutrinos collide with the charged particles in the water, which makes them travel at a speed higher than the speed of light in the medium, which is usually water, and therefore, are called Water-Cherenkov detectors [1,3].

In the walls of these detectors, special sensors called Photo-Multiplier Tubes (PMTs) are located and from them, we gather the light produced by the Cherenkov radiation for analysis, which usually comes in the form of a ring or cone. This analysis usually begins by determining features of the detected event such as the direction of travel of the neutrino and its energy before colliding with the particles in the water, and the class of the detected event, which is the main topic of the present paper and the project from which it is based on, where four deep learning methods: VGG19, ResNet50, PointNet and Vision Transformer, were implemented, each with its respective hyper-parameter tuning for the purpose of identifying which of the proposed methods worked best for the task of identifying the class of simulated neutrino events corresponding to a Water-Cherenkov detector called Intermediate Water Cherenkov Detector or IWCD. State of the art research considering custom CNNs and a ResNet50 model with different hyper-parameters to the ones shown in this project, have provided an accuracy of approximately 70% and an Area Under the Curve (AUC) for the efficiency plot of 0.77 at best [4, 5].

With the development of this project we observed that the model which provided the best results was ResNet50 as it gave an accuracy of 72.48% and an AUC for the efficiency plot of 0.71, while also minimizing the needed for computational resources. Moreover, we observed that, regarding the data, the bigger the dataset the better the results as then, we have enough samples of different types of events within each class to assure the employed architectures can learn them. Additionally, for hyper-parameter tuning we had to employ smaller samples of the largest dataset as it contained more than a million events per class, from this it was determined that the samples have to be taken randomly and should not be ordered therefore assuring the models learnt better.

In this paper we have 5 sections, in section 2 we talk about the employed methodology and the data we used, to then, show and explain our results in section 3. After this, in sections 4 and 5 we provide the discussion and conclusions of the developed project, respectively.

2 Methods

The overall process followed to obtain the models with which we processed our data as well as a brief description of the employed dataset is found in this section.

2.1 Data

As was mentioned in the Introduction, the data we employed was simulated and corresponds to the IWCD tank, a Water-Cherenkov detector 8m tall, with a diameter of 10m and 536 mPMTs along its walls, at the moment the data was simulated, where mPMTs are circular structures composed by 19 of the PMTs mentioned in the previous section, this allows to maximize the detection of the Cherenkov light produced by the occurrence of a neutrino event. All events are of a single ring type, which means we have only one class per event, which can be one of three: gamma, electron or muon.

All event data is stored within two supercomputing clusters: CADS located at Universidad de Guadalajara in Mexico, and Cedar located at Simon Fraser University in Canada. The number of events per class for each of the dataset located in these two clusters can be seen in Table 1.

2.2 Methodology

As for the methodology we employed to obtain the different models to classify the neutrino events, this can be observed in the diagram shown in Figure 1. As can be seen, the process of training, validating and testing the architectures is done recursively as we had to tune their hyper-parameters, which was done by analyzing the values obtained for the metrics listed at

Table 1: Number of events per class per supercomputing cluster

Database	Class	Number of events per particle
CADS	gamma	9k to 3M
	electron	9k to 3M
	muon	9k to 3M
Cedar	gamma	∼8M
	electron	∼8M
	muon	∼3M

the last block in the diagram. The tuning process was made employing either the smaller datasets, which had 9k events per class or by taking a smaller sample of the larger datasets.

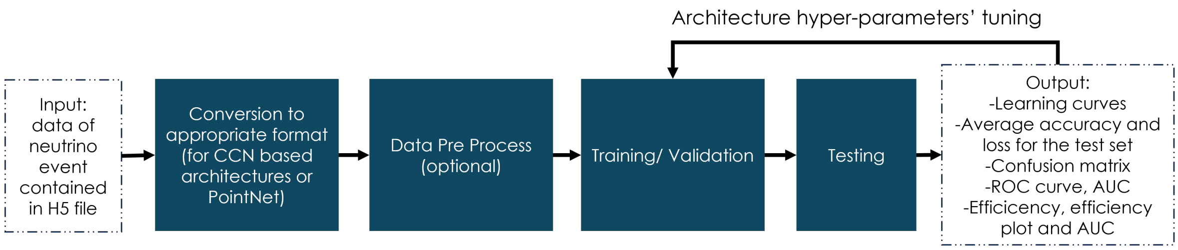

Figure 1: Block diagram of the followed methodology

As a result of the process depicted in the diagram, we obtained 10 different models considering a variation (employing pretrained weights) of one of the 4 implemented deep learning architectures, which were VGG19, ResNet50, PointNet and Vision Transformer, as well as modifications made to the dataset so as to try and improve the values of the classification metrics. These modifications were:

- Separating the dataset into muon and not muon class and then separating the not muon class into gamma and electron. This was done because the models, in general, have no problem telling apart the muon class from the other two, but gamma and electron are not easily separable and, therefore, the muon class was taken from the dataset from the beginning so that the models can focus in learning how to differentiate between gamma and electron.

- Considering only the events of type gamma and electron we filtered out those events in which a minimum number of pixels were not different from zero after converting the input data into an image and applying image processing techniques. This modification to the data was done because there are events within these two classes that had sparse detection of hits. This processing of the data was done with the smaller datasets and only considering the objective of improving the evaluation metrics of the models but, even though it did improve the results it also made the models biased to the events that form a ring, therefore, from a physics perspective is not effective. Nonetheless, as was mentioned before by employing the largest datasets we can mitigate the effect that events with sparse hits have on the learning of the models.

3 Results

To evaluate the models obtained from applying the process shown in Figure 1 we got different evaluation metrics which include the learning curves, average accuracy and loss from processing the test set by the trained and validated models, the confusion matrix, the Receiver Operating Characteristic (ROC) curves and their respective AUC, as well as the overall efficiency of the model, the efficiency curve and its AUC considering different classes as signal and as background. But, for the general objective of the project which was about finding which deep learning method worked best for the classification of neutrino events, we only show the following metrics for the gamma and electron classes, as the muon class is easily separable due to its higher energy in comparison with the other two:

- the efficiency plots with their respective AUC considering the electron class as signal and the gamma class as background
- the ROC curves with their AUC in a one vs. the rest approach

Thus, in Figure 2 we can see the efficiency plot obtained from considering the electron class as signal and the gamma class as background for all the models employed in the classification of these two classes.

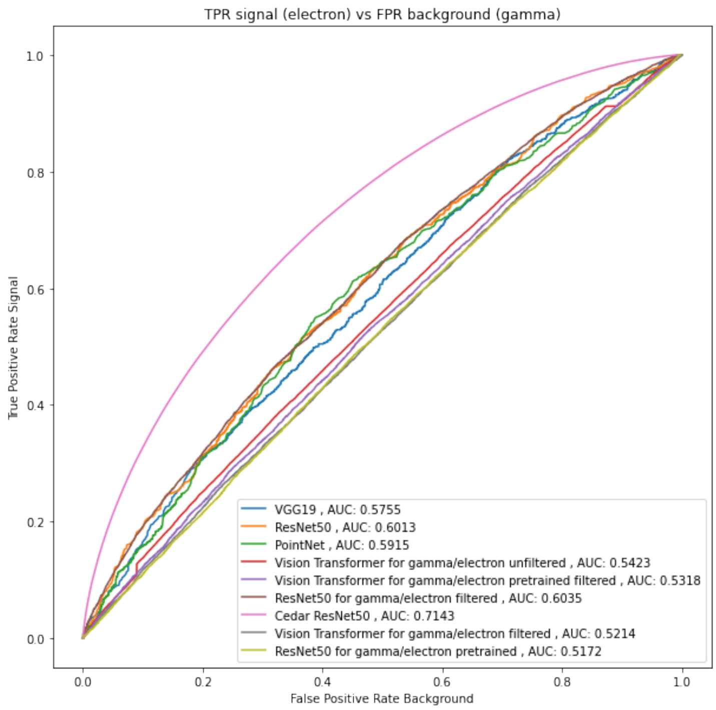

Figure 2: Efficiency plot for all models employed in the classification of the gamma (background) and electron (signal) classes

As we can see, the best results for the classification of these classes were obtained by employing the ResNet50 model to classify the dataset contained at the Cedar supercomputing cluster, since we had a curve with an AUC of 0.7143. These results were confirmed by analyzing the ROC curves and AUC values shown in Figure 3, where the curve that reaches a value of 1 for the true positive rate with a smaller value of false positive rate for both classes, which also meant a greater AUC value, was also with the ResNet50 model applied to the Cedar dataset. Moreover, we can also observe that ResNet50 did well with other datasets, which include the smaller ones located at CADS as well as the modifications done to the data like filtering by the number of pixels different from zero, although we have to mention that ResNet50 did perform poorly when using pretrained weights.

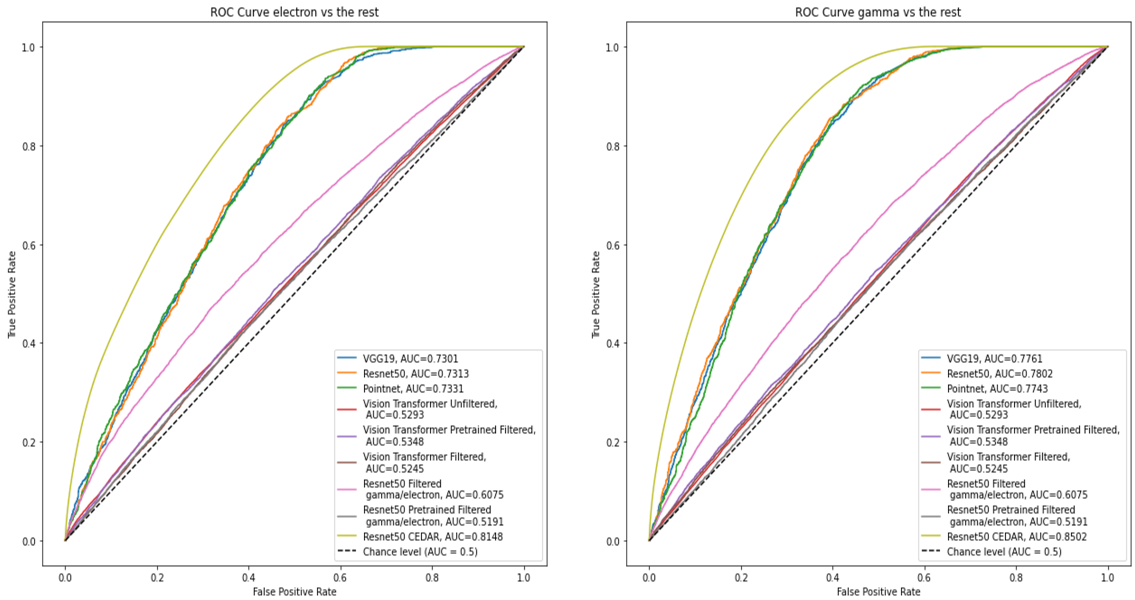

Figure 3: ROC curves and AUC for the gamma and electron classes in a one vs. the rest approach

4 Discussion

Our research has shown that out of all the models we applied to the task of classifying neutrino events, ResNet50 provided the best results, which was consistent throughout all the applications and modifications that were made to the dataset, except when using pretrained weights for this architecture, which showed that pretrained weights are useful depending on the application. Moreover, these results considerably improved when the largest dataset was employed which also solved the situation of having biased data after applying the filtering by number of pixels different from zero, which, in turn, showed that events with sparse hits do not pose a problem for the classifiers as long as we have a large enough sample of these types of events.

When sampling from the largest datasets, its is essential to take random samples and should not be sorted by the values of any of the variables which describe the event, thus allowing the representation of all types of events, this is, those that form rings and those that have sparse hits, in the sample.

Finally, regarding the filtering of the events by counting the number of pixels different from zero after transforming the event data to an image and applying image processing techniques, we ought to mention that it did improve the classification metrics since, in this way, events that did form a ring could be better separated into gamma and electron, nonetheless, we cannot assure that within the detector we will only have these types of events since there could be events with a physical feature, such as the energy or direction of travel, whose values are within a specific range that will always provide sparse hits within the detector or it could be that the collision of the neutrino with the charged particles in the water occurred at a location within the tank which also makes that the detector could only get sparse hits from the event. Therefore, in this sense, further research should be done to the data so that we can conclude what are the conditions of an event with detection of sparse hits so that we can assure we should use it or not.

5 Conclusion

While the main objective of our research was to determine which of the proposed deep learning architectures worked the best for the purpose of classifying neutrino events, we could also observe how important getting to know our data was to get conclusive results. Thus, ResNet50 provided the best and most consistent results except when using pretrained weights, obtaining an accuracy of 72.48% and an AUC for the efficiency plot of 0.71 for our best model, nonetheless, we can get better results when we have enough of all types of neutrino events for all classes, specially gamma and electron, which are easily misclassified among themselves. Further research should be done to the conditions surrounding the detection of events that form a ring and those that do not so that this could be taken into account during analysis.

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