Deep learning for Directional Dark Matter search

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Introduction

One of possible Dark Matter (DM) candidates are Weakly Interacting Massive Particles (WIMPs) with the possible masses ranging from several GeVs to TeVs and the interaction cross section with ordinary matter around the weak scale. We study the signal purification in DM direct detection experiments with Deep learning, using the NEWSdm experiment (Nuclear Emulsions for WIMP Search, directional measure [1]) as a benchmark.

Directional detection

Within the DM galactic halo model probing the direction of the DM induced nuclear recoils can give the unambiguous signature of DM interaction. Moreover, the information about directionality can allow us to go below the "neutrino floor".

To extract the information about the tracks below the resolution of the optical microscope the polarised light is used. The idea is based on the Plasmon resonance effect [2].

Experimental data

Training and test data is acquired by exposure of real emulsions to a specific source. Tracks from DM-nucleus interactions are simulated with Carbon ion beam with fixed energy (30-100 keV). The background is represented by different gamma radiation samples and thermal fluctuations ("fog"). Each sample consists of $\sim 10^5$ tracks, each of them having 8 monochromatic polarisation images for different light polarisation angles in the microscope during scanning. Figures 1 and 2 explicitly demonstrates the Plasmon resonance effect on different track types.

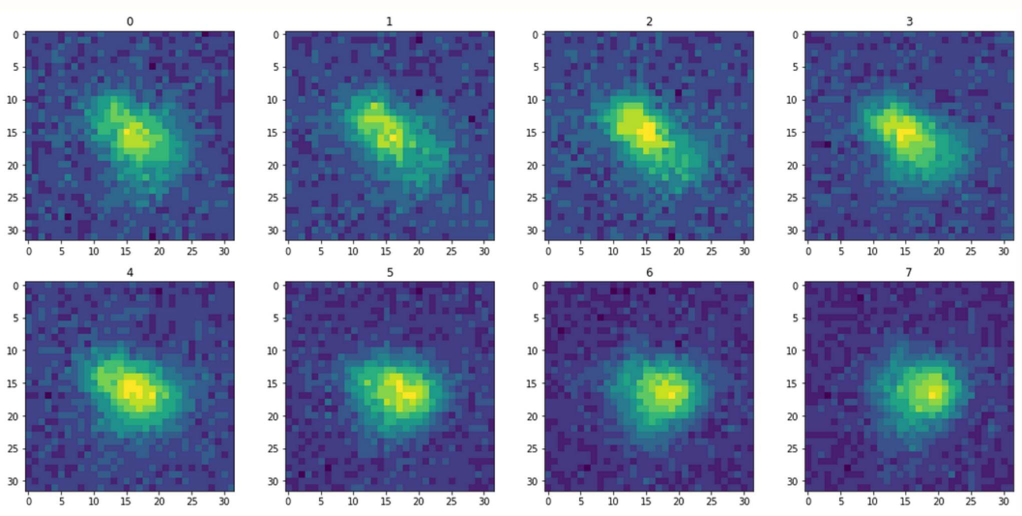

Figure 1: 8 images of a single Carbon 100keV track with different light polarisation

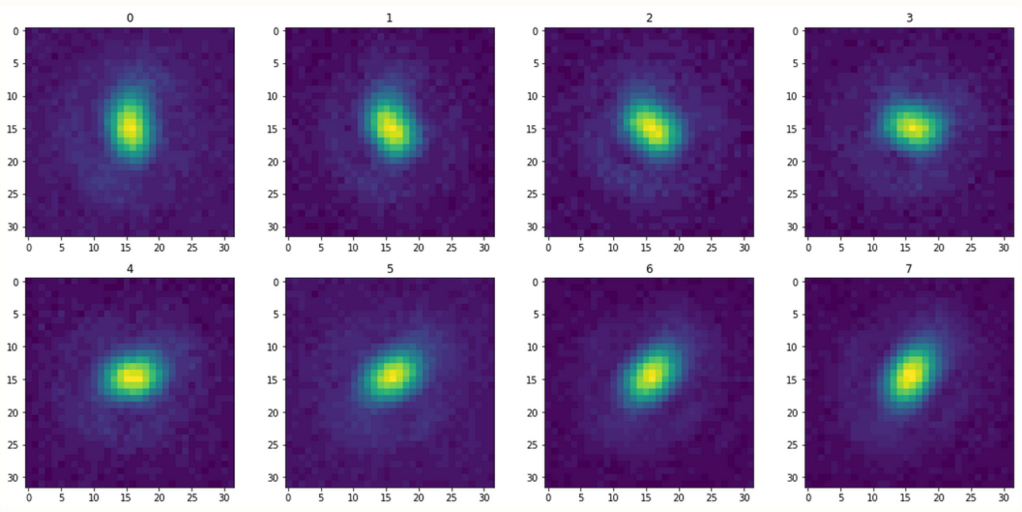

Figure 2: 8 images of a single fog background track with different light polarisation

Network and approach

We use Convolutional Neural Networks (CNNs) for the signal-background classification. Our goal is the best background separation.

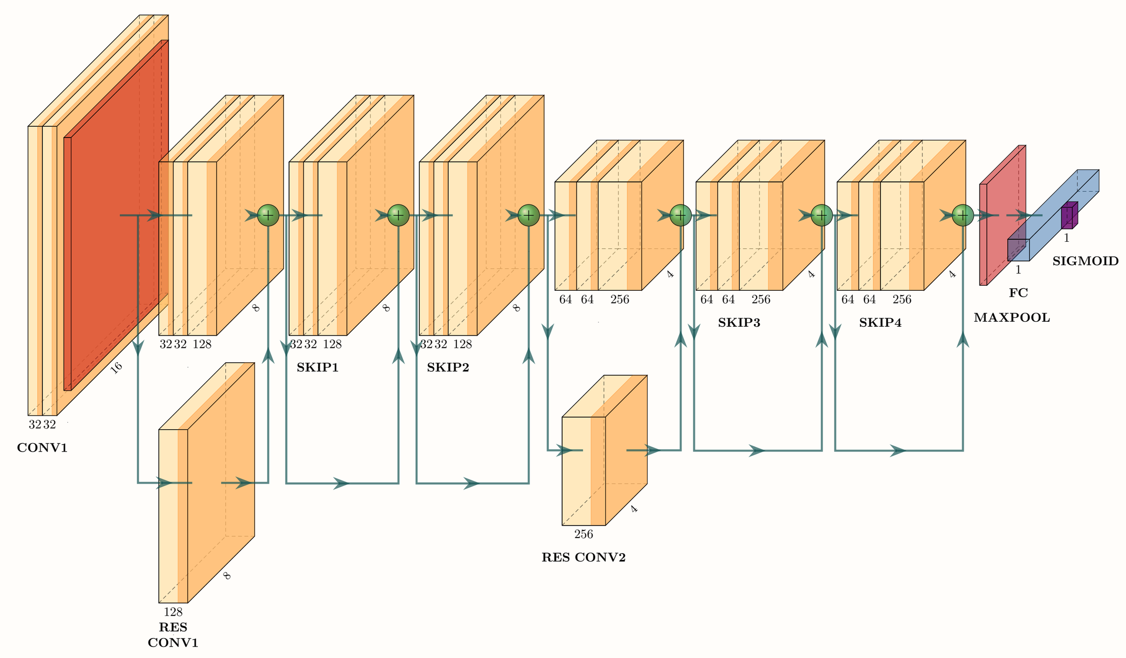

Figure 3: The CNN architecture. $3\times3\times3$ and $1\times1\times1$ filters are used.

Periodic boundary conditions

8 different light polarisation angles covers the whole 180° rotation. This means "polarisation axis" has to be periodic and after the 8th image must come 1st. To imply this we add 9th image which is a copy of the 1st. This allows network to explore correlations between 8th and 1st polarisation images as between neighbours.

3D CNN

It is important to explore the correlations between different polarisation images for the same track, therefore we stacked 8 images into a big 3D image and use 3D CNN architecture to explore features in the "polarisation axis".

Track rotations

The direction of the track is an important physical feature, that should be checked after selecting a signal candidate to verify its DM origin. Hence we apply random 2D rotations to each training batch to make training data isotropic and be sure that network is not using directionality as a distinctive feature. All 9 polarisation images of a track are rotated together.

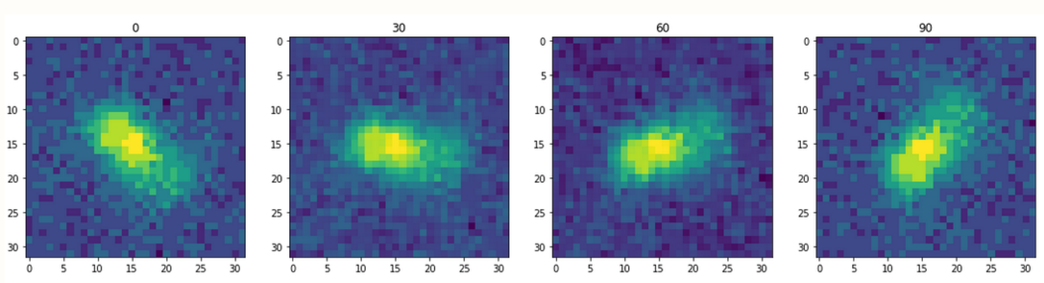

Figure 4: Example of the rotations of a single Carbon track polarisation image.

References

[1] A. Aleksandrov, et al. "NEWS: Nuclear Emulsions for WIMP Search." *arXiv:1604.04199*

[2] Alexandrov, A., et al. "Development of a super-resolution optical microscope for directional dark matter search experiment." *DOI:10.1016/j.nima.2015.09.044*

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Background rejection

The default output of the algorithm for a track is a probability of being signal. To construct an algorithm with binary output and compute the metrics we need to specify a threshold on the probability output. The metrics we use are background rejection (all input "background" divided by false "signal") and efficiency (true "signal" divided by all input "signal").

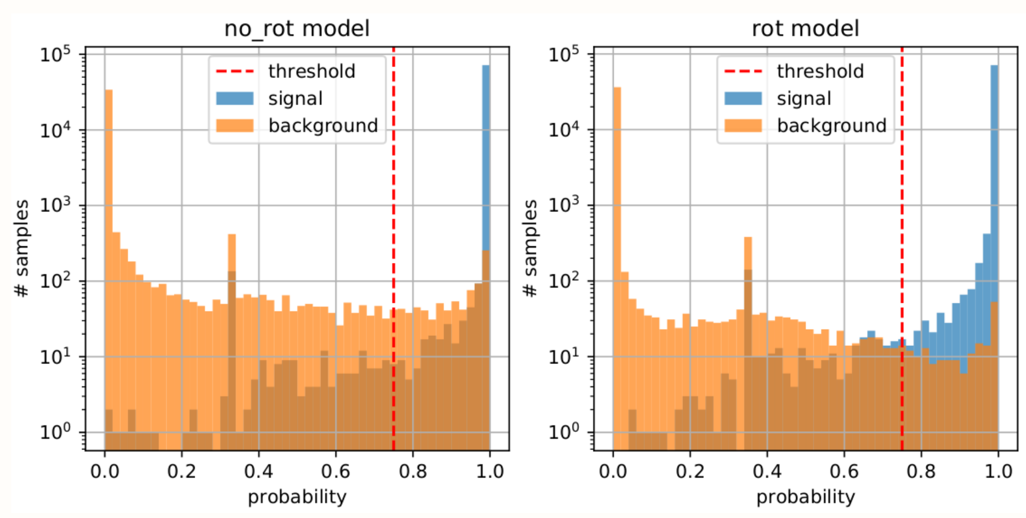

Figure 5: Network's output on a test sample for Carbon 100keV against fog. Red line demonstrates a possible probability threshold.

Currently required background rejection level for the NEWSdm experiment is $\sim 10^4$ with the efficiency of $\gtrsim 0.6$. We compare the test performance of the models trained with and without image rotations.

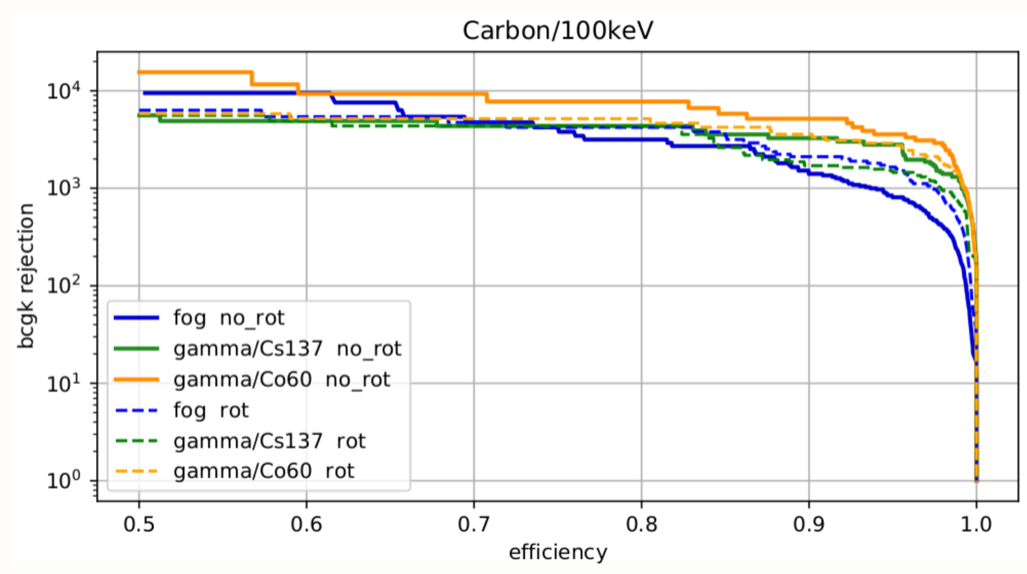

Figure 6: Background rejection - efficiency plot for Carbon 100 keV against various types of background. Different points on the curve correspond to different threshold values for the output.

Summary and conclusions

We studied signal-background classification with CNNs in the DM search experiment. Applying physical motivation both to the network's architecture and data preprocessing approaches the experimentally required 10^4 background rejection power. Implying isotropy condition with random rotations does not hurt the performance and gives benefits for further physical analysis of the sample.