Imperial College London

IDENTIFICATION OF ANTINEUTRINOS AT SOLID USING CONVOLUTIONAL NEURAL NETWORKS

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BACKGROUND

WHAT IS SoLid?

SoLid is a reactor-based neutrino detector which detects anti-neutrinos through **inverse beta decay (IBD)** $\overline{\nu}_e + p \longrightarrow e^+ + n$. The overall goal of SoLid is to measure the energy spectrum and flux of anti-neutrinos as a function of distance to be used in the search for **sterile neutrinos** [1].

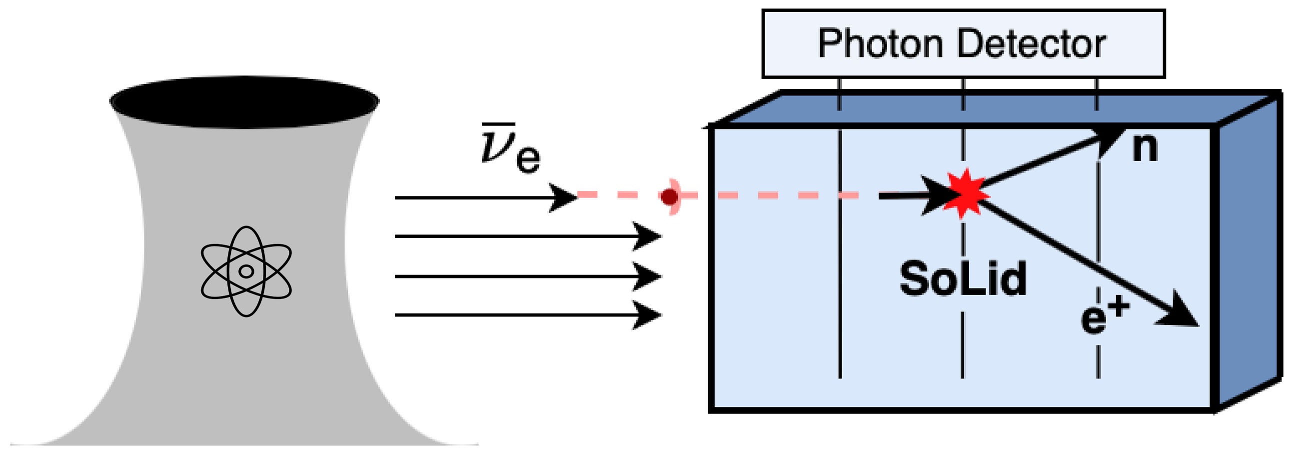


Fig 1. Reactor anti-neutrinos are captured by SoLid and undergo IBD.

By looking for coincidences of the two decay products in the detector, IBD candidates can be identified.

The detector is composed of scintillation cubes, arranged in a 3D grid. Since the detector is at sea level and is next to a reactor, there is a lot contamination which must be separated from the signal [1].

WHAT IS MACHINE LEARNING?

Machine learning (ML) is a technique in which a program teaches itself how to perform a task without every step being explicitly programmed. Often, it is used to find patterns in data.

Convolutional Neural Networks (**CNN**s) are a type of ML algorithm. They use convolutional kernels to scan large amounts of data quickly and look for local correlations in data. CNNs are very applicable to data in the form of images.

- SoLid presents a **categorisation problem**. Is a given event signal or background?

RESEARCH AIM

- To implement a 2D and a 3D CNN algorithm for anti-neutrino identification/background rejection at SoLid.
- To explore that capabilities of different types of architectures.

DATA

- Data from detector (+ simulated signal) is reconstructed as 3D images with brightness determined by in the cube.
- The CNN is easier to train on 2D images, so at first projections of the 3D image were made. Then the full 3D reconstructions were also used for training.

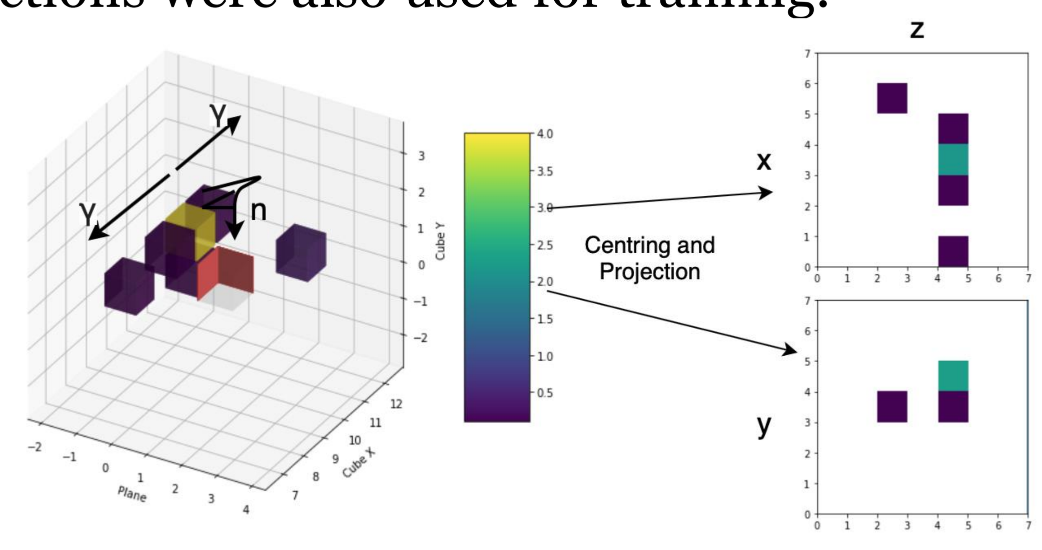
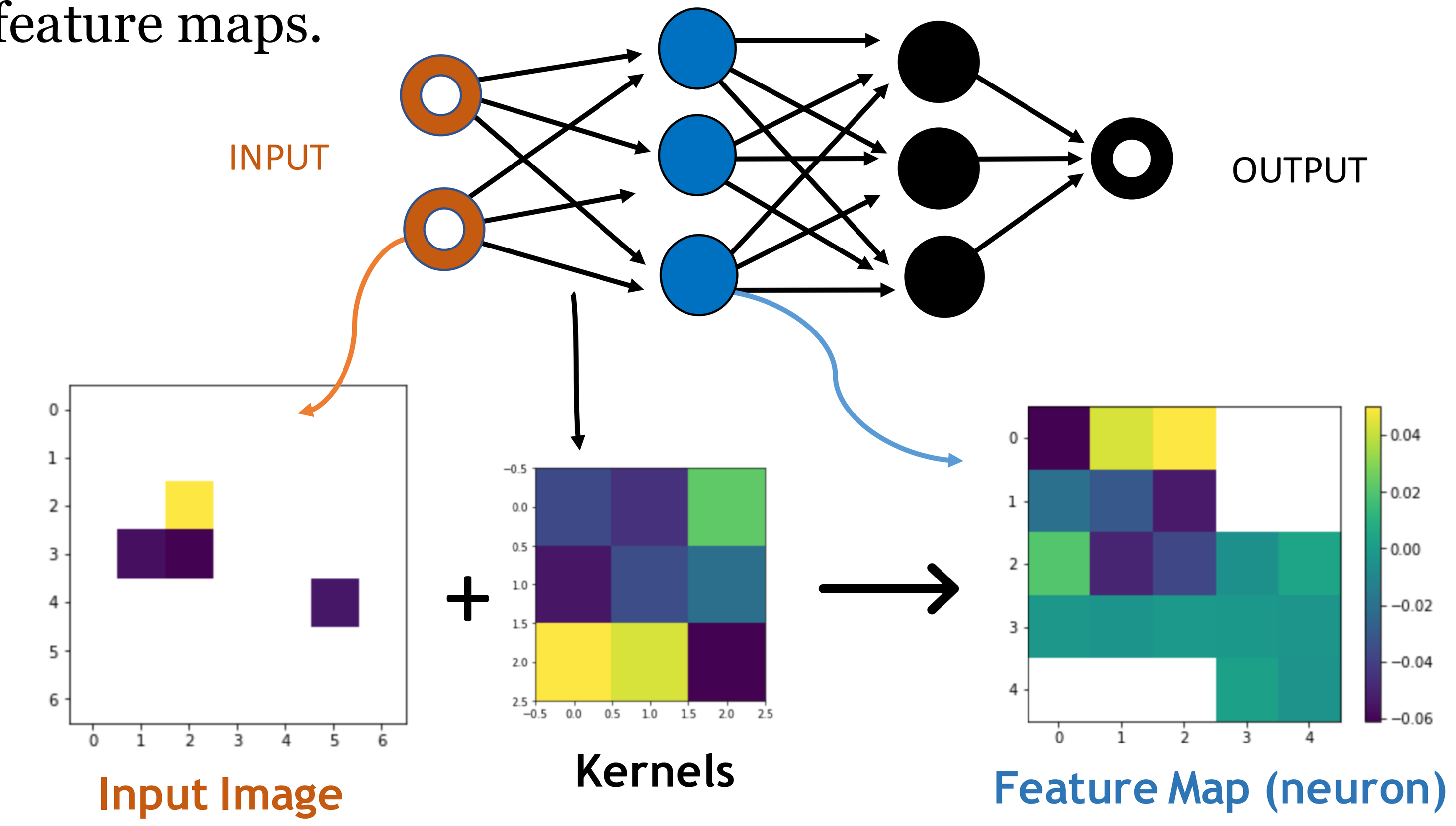


Fig 2. 3D and 2D reconstruction of an IBD event.

- Different backgrounds studied: Reactor off, Accidental, Bismuth-Polonium Decay, Atmospheric Neutrons.

ARCHITECTURE

The input image is convolved with a kernel to produce feature maps.



The kernel is a set of weights which the CNN varies such that the feature maps produced can pick out properties which distinguish signal from background. By studying the kernel, we can understand what the CNN has learned.

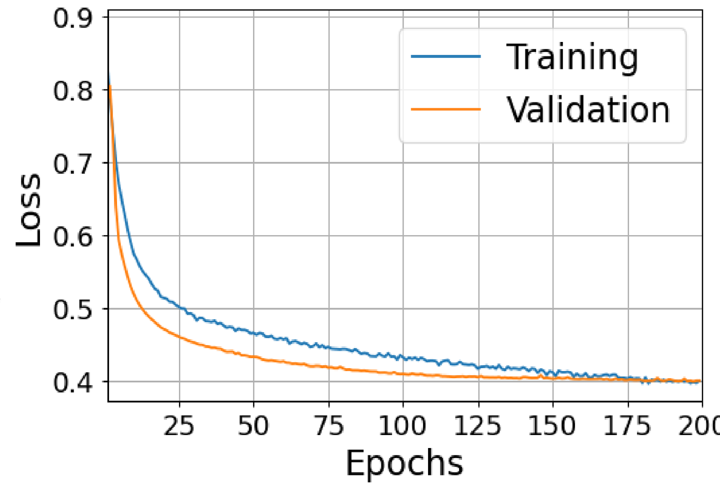
Hyperparameters (such as the learning rate, the number of neurons, the size of the kernel, etc.) must be tuned to obtain the best learning.

Note: over-complicated models fail to generalise (overfit).

CNN RESULTS

Training was monitored, and it was found that 3 layers of 10 neurons worked well for the 2D images. **Good classification** was achieved as shown below (for 2D CNN Reactor Off background and 7x7 input images).

Fig 3. Loss decreasing over training time (epochs). The training is smooth and generalising well.



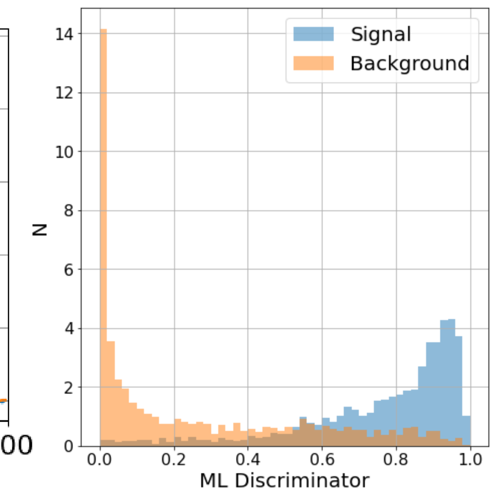


Fig 4. Classification histogram showing signal and background separation.

ROC curves show the true positive rate against the false positive rate for binary classification. The maximum area under the curve (**AUC**) is 1 which is perfect classification. It is an important metric to compare classifiers.

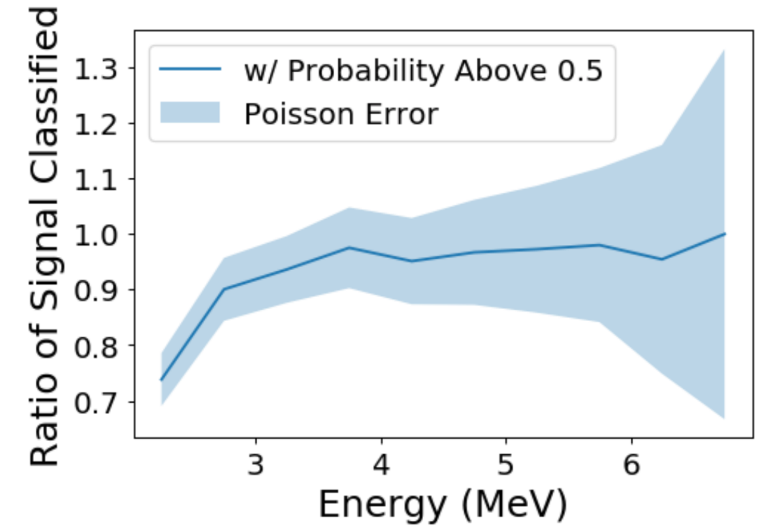


Fig 5. Classification dependence on energy will bias the results of the experiment therefore a flat response is desired.

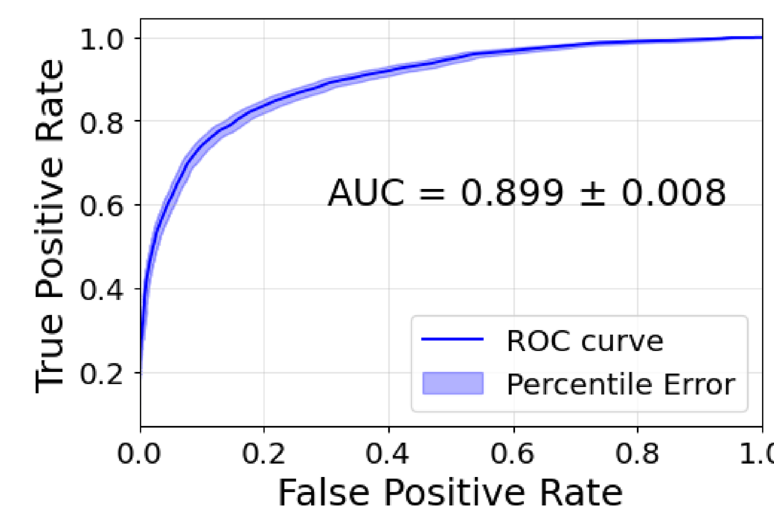


Fig 6. ROC curve showing AUC value.

t-distributed Stochastic Neighbour Embedding (**t-SNE**) is a tool for visualising the shape of high-dimensional data [2]. It is used to visualise the values of the neurons from each image in 2D.

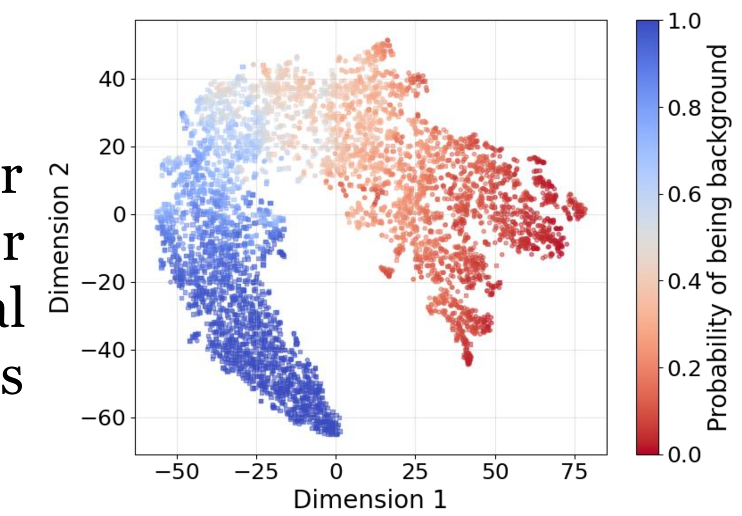


Fig 7. t-SNE visualisation for last dense layer.

Larger input images were also studied along with 3D CNNs, which resulted in consistent classification and some improvements.

The effect of hand-crafted data included in the final layer was also studied.

CONCLUSION

- Both 2D and 3D CNNs have successfully classified the data with good accuracies and AUC.
- This method could be implemented alongside others in an ensemble used at SoLid, however further analysis is required to check the energy response and to further constrain hyperparameters.

REFERENCES:

[1] SoLid Collaboration, Y. Abreu, Y. Amhis, et al. SoLid: A short baseline reactorneutrino experiment.arXiv:2002.05914, March 2020.

[2] Laurens van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of Machine Learning Research (JMLR)*, 9(Nov):2579–2605, 2008.