Machine learning assisted neutron-γ discrimination for a plastic scintillator detector

S. Panda[1,2,*] P. K. Netrakanti[1], S. P. Behera[1,2], R. R. Sahu[1],
K. Kumar[1,2], R. Sehgal[1], D. K. Mishra[1,2], and V. Jha[1,2]
[1] *Nuclear Physics Division, Bhabha Atomic Research Centre, Mumbai - 400085, INDIA and*
[2] *Homi Bhabha National Institute, Anushaktinagar, Mumbai - 400094, INDIA*

Introduction

Pulse shape discrimination (PSD) via the charge comparison method (CCM) is an effective technique for particle identification in nuclear and particle physics experiments. In reactor neutrino [1] and rare-event search experiments, fast neutrons act as a major background, which are identified by PSD CCM. However, CCM deteriorates at lower energies, limiting the neutron-γ separation. In this work, we have investigated machine learning (ML) algorithms to enhance the low-energy PSD using plastic scintillator data, benchmarked against time-of-flight measurements.

Data Analysis

Experimental data was collected using an EJ-276D plastic scintillator (PS) with PSD capability. The detector was optically coupled to a Hamamatsu R7724, 10 stage photomultiplier tube, operated at a negative bias of 1200 volts. To collect neutron-γ waveforms, an AmBe neutron source was used. Additionally, to calibrate the detector, ^{137}Cs and ^{22}Na γ-ray sources were used. Offline pulse processing was done to extract different information like total charge, short gate (SG) and long gate (LG) from the raw waveform. The PSD from charge-comparison-method was calculated using tail-to-total charge ratio technique, which is given by $\mathrm{PSD} = 1 - \frac{\mathrm{Q_S}}{\mathrm{Q_L}}$. Figure 1 represents PSD as a function of integrated charge. The top axis shows the deposited electron-equivalent energy ($\mathrm{E_{dep}}$) by the interacting particle in the detector medium.

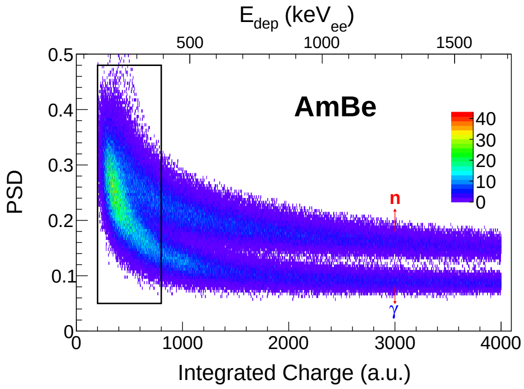

FIG. 1: PSD is shown as a function of integrated charge. Top axis represents the electron-equivalent deposited energy.

The figure of merit given by $\mathrm{F.o.M} = \frac{|\mu_\gamma - \mu_\mathrm{n}|}{\mathrm{FWHM}_\gamma + \mathrm{FWHM}_\mathrm{n}}$ defines the neutron-γ separation ability of the detector. Where, $\mu_{\gamma,\mathrm{n}}$ are the mean values and $\mathrm{FWHM}_{\gamma,\mathrm{n}}$ is defined as the full width at half maxima for γ and neutron events. For the optimal gate setting, in the integrated charge range 1500 to 4000, F.o.M was found to be 1.21. The higher $\mathrm{E_{dep}}$ region showing better discrimination, whereas the lower $\mathrm{E_{dep}}$ region (highlighted within the black rectangle in Fig.1) has substantial overlap. To overcome this limitation, ML algorithms are utilized to improve discrimination, particularly in the low energy regime.

For ML input, three physically motivated variables were prepared by integrating charge (a.u.) in different regions of the waveform, which are R_{head}, $\langle t \rangle_Q$(in ns) and $k\sigma^2$ [2]. Where R_{head} is the total integrated head charge within 48-68 ns, $\langle t \rangle_Q$ is the charge-

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[*] Electronic address: `srpanda@barc.gov.in`

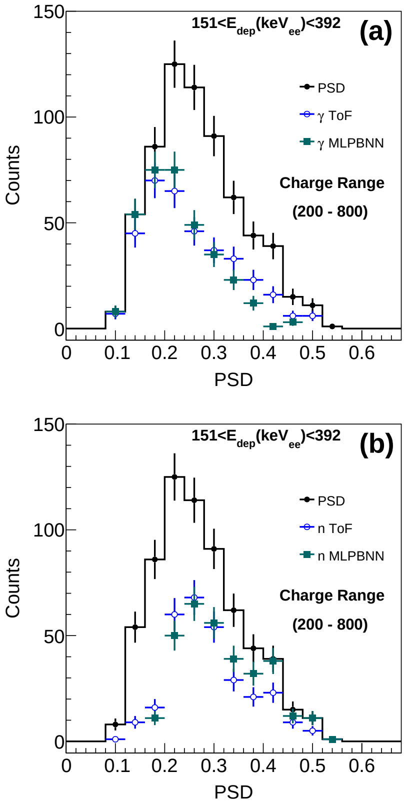

FIG. 2: Comparison of PSD distribution between CCM (black), γ (neutron) tagged events (blue circle) from ToF and from the MLPBNN score (green squares).

weighted mean time in 78-108 ns, and k is defined as the *kurtosis*, a measure of the relative tailedness of a distribution. The variable $k\sigma^2$ is tested to have better ranking in terms of separation. These input parameters along with the bias node are used in the training process.

Machine Learning

In this work two ML algorithms are studied, the traditional form of Multilayer Perceptrons with Bayesian approach (MLPBNN) and Support Vector Machine (SVM). The ML algorithms are implemented using the TMVA toolkit that is available in ROOT framework. An input dataset was prepared by considering a PSD-based data driven model. Taking PSD in different $\mathrm{E_{dep}}$ ranges into account, a model $(kSigma)_{n,\gamma}$ was used for initial labeling of neutron and γ events. The dataset was split into a 20:80 ratio for testing and training, respectively. From the training weights, R_{head}, $\langle t\rangle_Q$ and $k\sigma^2$ are calculated for each waveform on event-by-event basis and optimal cuts are obtained by calculating the significance. The optimal cut values are applied on the full dataset to separate out the γ and neutron events.

Results and Discussion

To verify the results obtained from the ML algorithms at lower energy ranges, a Time-of-flight (ToF) experiment was performed, where the neutron-γ events are linearly separable in the time domain. For the ToF experiment, a $\mathrm{CeBr_3}$ detector was used as the start time detector because of its excellent energy resolution ($\sim$ 4% at 0.662 MeV). The same PS detector, placed at 1 meter distance, was used as the stop time detector.

The selected γ and neutron events in the low energy deposition regime are compared with the ML predicted γ and neutron events, to check the effectiveness of the model. Figure 2 shows the comparison between the true events extracted from the ToF measurement and the ML predicted events for MLPBNN algorithm. The ML predicted events show a reasonable agreement with those identified by ToF. The classification accuracy is estimated to be 0.79 and 0.80 for SVM and MLPBNN, respectively.

Conclusion

This study applies two ML algorithms, MLPBNN and SVM to improve neutron-γ discrimination in a PS with PSD property where traditional method fails. The model uses three variables to extract features from the raw waveform. The ML output was validated using a ToF experiment down to 151 $\mathrm{keV_{ee}}$.

References

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