Abstract: The Indian Scintillator Matrix for Reactor Anti-Neutrino detection - ISMRAN experiment aims to detect electron anti-neutrinos ($\bar{\nu}_e$) emitted from a reactor via inverse beta decay reaction (IBD). The setup, consisting of 1 ton segmented Gadolinium foil wrapped plastic scintillator array, is planned for remote reactor monitoring and sterile neutrino search. The detection of prompt positron and delayed neutron from IBD will provide the signature of $\bar{\nu}_e$ event in ISMRAN. The number of segments with energy deposit ($N_{\text{bars}}$) and sum total of these deposited energies are used as discriminants for identifying prompt positron event and delayed neutron capture event. However, a simple cut based selection of above variables leads to a low $\bar{\nu}_e$ signal detection efficiency due to overlapping region of $N_{\text{bars}}$ and sum energy for the prompt and delayed events. Multivariate analysis (MVA) tools, employing variables suitably tuned for discrimination, can be useful in such scenarios. In this work we report the results from artificial neural network classifier - the multilayer perceptron (MLP), particularly the Bayesian extension - MLPBNN, to achieve better signal detection efficiencies with reasonable background rejection. The neural network response is used to distinguish prompt positron events from delayed neutron capture events on Hydrogen, Gadolinium nucleus, and from a typical reactor $\gamma$-ray background. A prompt signal efficiency of $\sim91\%$ with a reasonable background rejection of $\sim73\%$ is achievable with the MLPBNN classifier for the ISMRAN experiment.

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1 Introduction

In recent years, the measurement of reactor based anti-neutrinos ($\bar{\nu}_e$) has provided key aspects in understanding the nature of neutrino interactions and their oscillations. Results from experiments like Daya bay collaboration have reported precise measurements of $\theta_{13}$ mixing parameter [1] and possibility of searches for light sterile neutrinos [2]. Also an excess of events, in energy region $\sim$5 MeV, observed in the prompt event spectrum of the reactor $\bar{\nu}_e$ induced inverse beta decays (IBD), has opened up new avenues for further studies in reactor based $\bar{\nu}_e$ [3–5]. Various experiments, using moderate scale (few tonnes) detector, are being proposed or taking data at very short baselines to further understand the properties associated with the reactor anti-neutrinos [6–9]. The Indian Scintillator Matrix for Reactor Anti-Neutrinos (ISMRAN) experiment is one such detector consisting of plastic scintillator (PS) bars in an array forming an active detection volume of 1.0 ton by weight [10]. ISMRAN is proposed to measure reactor $\bar{\nu}_e$s for non-intrusive monitoring of reactor along with the possibility of very short baseline oscillation searches of $\bar{\nu}_e$ to sterile states [11]. ISMRAN is an above ground experiment comprising of 100 PS bars, each of dimension 100cm $\times$ 10cm $\times$ 10cm. Each PS bar is wrapped with Gadolinium oxide (Gd$_2$O$_3$) coated aluminized mylar foils (areal density of Gd$_2$O$_3$: 4.8mg/cm$^2$) and directly coupled to a 3” PMT at both ends. A 10 cm thick lead (Pb) and 10 cm thick borated polyethylene (BP) shielding will enclose the full setup along with the use of muon veto scintillators on all sides outside the shielding structure. The location of ISMRAN is at a distance of $\sim$13m from 100 MW$_{th}$ Dhruva reactor [12] core on a trolley based structure for allowing movement of the detector to various distances from the reactor core. A schematic of complete ISMRAN setup is shown in Fig. 1. A high sampling rate (500 MS/s) digitizer based DAQ has been chosen for recording the output from the 200 PMT channels and the acquisition is performed with minimum thresholds for offline event reconstruction.

Detection of $\bar{\nu}_e$s from nuclear reactor is primarily done using the IBD reaction which has a $\bar{\nu}_e$ energy threshold of 1.806 MeV. In this reaction an $\bar{\nu}_e$ interacts with a proton in the detector volume
Figure 1. Schematic diagram of ISMRAN detector, 100 PS bars, inside a shielding of 10 cm of lead and 10 cm of borated polyethylene on a mobile trolley. Outside the shielding structure are the muon veto scintillator detectors.

(usually a scintillator) and produces positron and neutron as:

\[
\bar{\nu}_e + p \rightarrow e^+ + n.
\]  

The positron deposits energy in the detector volume, via ionization, followed by production of two \(\gamma\)-rays of 0.511 MeV each, from its annihilation with an electron. These \(\gamma\)-rays then deposit their energy through Compton scattering. These energy deposits from positron and the resulting annihilation \(\gamma\)-rays forms the prompt event.

\[
n + p \rightarrow d^* \rightarrow \gamma, \quad E_\gamma = 2.2 \text{ MeV}, \quad \sigma_{n\text{-}\text{capture}} = 0.3 \text{ b},
\]
\[
n + ^{155}\text{Gd} \rightarrow ^{156}\text{Gd}^* \rightarrow \gamma^{'s}, \quad \sum E_\gamma = 8.5 \text{ MeV}, \quad \sigma_{n\text{-}\text{capture}} = 61000 \text{ b},
\]
\[
n + ^{157}\text{Gd} \rightarrow ^{158}\text{Gd}^* \rightarrow \gamma^{'s}, \quad \sum E_\gamma = 7.9 \text{ MeV}, \quad \sigma_{n\text{-}\text{capture}} = 254000 \text{ b}.
\]

Meanwhile, the neutron having few keVs of energy undergoes thermalization in the detector volume and gets captured on either Gd or H nuclei. The capture of neutron on H will produce a mono-energetic \(\gamma\)-ray of 2.2 MeV as shown in equation 2. On the other hand, the neutron capture on Gd leads to an emission of cascade \(\gamma\)-rays as shown in equations 3 and 4. Due to very high thermal neutron capture cross-section (\(\sigma_{n\text{-}\text{capture}}\)) of Gd, the capture event has higher probability to take
place on the wrapped Gd foil than in the hydrogenuous bulk of the scintillator. In recent years, a great amount of experimental and theoretical work is done in understanding and improving the modeling of the de-excitation of Gd nucleus and emission of cascade $\gamma$-rays particularly in context of IBD events [13–15]. The capture of neutron happens after a mean time delay, ranging from a few $\mu$s up to an order of a few 100 $\mu$s, from the positron event depending on the capture agent position and its concentration in the detector volume. The energy deposited by cascade $\gamma$-rays from these capture, form a delayed event. Electron anti-neutrino events in the detector volume are therefore identified through the detection of these prompt and delayed event pairs separated in time. For a segmented detector geometry like ISMRAN, it is possible to record the hit patterns and energy deposition profile of annihilation and capture $\gamma$-rays. This is a useful feature for classifying the events as either prompt or delayed based on differences in $\gamma$-ray event topologies and energy depositions [10]. Moreover, it also helps in discriminating these events from the cosmogenic backgrounds. In a typical reactor environment, the signals produced due to the $\gamma$-rays and neutron background in the vicinity of the setup can be misidentified as either prompt or delayed event in the detector.

2 Simulated IBD events in ISMRAN

To understand the IBD event characteristics and the corresponding signal detection efficiencies in ISMRAN, Monte-Carlo based IBD events are generated using GEANT4 [16] (version 4.10.4). The physics processes listed in QGSP_BIC_HP are used along with the inclusion of photon evaporation model for the de-excitation of Gadolinium nucleus and the resulting $\gamma$-ray cascade. The simulations are performed using the parameterization of $\nu_e$ spectrum from ref [17], the cross-section calculations from ref [18, 19] and the fission fractions for different isotopes from ref [20]. The two primary variables used in the event identification are the sum of the energy deposits and the number of PS bars ($N_{\text{bars}}$) with these energy deposits. These variables are separately recorded for the prompt as well as the delayed events for each simulated IBD interaction in ISMRAN. Only PS bars with

![Figure 2](image-url)  

Figure 2. Panel (a) Sum Energy and (b) $N_{\text{bars}}$ distributions for prompt and delayed events obtained from Geant4 simulation for IBD events in ISMRAN.
deposited energy above the threshold: $E_{\text{Th}}^{\text{bar}} = 0.2 \text{ MeV}$ are considered due to the minimum operating threshold of the signal in the real experiment. Figure 2 (a) shows the sum energy and 2(b) the $N_{\text{bars}}$ distributions with threshold condition for both prompt and delayed events. A significant overlap can be seen in both the distributions for prompt and delayed events. The $\bar{\nu}_e$ signal detection efficiencies for a simple cut based selection of the prompt and delayed events based on sum energy and $N_{\text{bars}}$ are shown in table 1 from these simulated events [10]. For obtaining reasonable discrimination between prompt and delayed events, the requirement of keeping both prompt and delayed event domains exclusive of each other using the criteria: $1 < N_{\text{prompt bars}} < 4$ on the prompt event and $N_{\text{delayed bars}} > 3$ on delayed event drastically reduces the $\bar{\nu}_e$ detection efficiency. Moreover, these stringent cuts cannot ensure complete exclusivity of the sum energy variable in prompt ($E^{\text{prompt}}$) and delayed events ($E^{\text{delayed}}$). PANDA experimental setup, using an array of 100 plastic scintillator bars have reported detection efficiency of 11.6% from simulations [9]. To obtain higher $\bar{\nu}_e$ detection efficiencies by

| Loose cuts | Stringent cuts | Efficiency (%) |
|------------|----------------|----------------|
| $1.8 < E^{\text{prompt}} (\text{MeV}) < 8.0, 1 < N_{\text{prompt bars}} < 4$ | $2.2 < E^{\text{prompt}} (\text{MeV}) < 8.0, 1 < N_{\text{bars}}^{\text{prompt}} < 4$ | 69 | 67 |
| $0.8 < E^{\text{delayed}} (\text{MeV}) < 8.0, N_{\text{delayed bars}} > 3$ | $3.0 < E^{\text{delayed}} (\text{MeV}) < 8.0, N_{\text{delayed bars}} > 3$ | 29 | 27 |
| $1.8 < E^{\text{prompt}} (\text{MeV}) < 8.0, 1 < N_{\text{prompt bars}} < 4, 0.8 < E^{\text{delayed}} (\text{MeV}) < 8.0, N_{\text{delayed bars}} > 3$ | $2.2 < E^{\text{prompt}} (\text{MeV}) < 8.0, 1 < N_{\text{prompt bars}}^{\text{bars}} < 4, 3.0 < E^{\text{delayed}} (\text{MeV}) < 8.0, N_{\text{delayed bars}} > 3$ | 20 | 18 |

using the sum energy and $N_{\text{bars}}$ variables, one needs to relax the selection criteria on these variables. This may lead to increase in the fake rate contribution, from natural backgrounds ($^{40}\text{K}$ and $^{208}\text{TI}$) and those from the ambient $\gamma$-ray activity mostly coming from the neutron captures in the vicinity of the detection setup in reactor hall. By performing multivariate analyses (MVA), using the sum energy and $N_{\text{bars}}$ variables, one can enhance the discrimination of the prompt signal from the above mentioned backgrounds improving the $\bar{\nu}_e$ detection efficiency. The event classifiers used in this approach can either be based on multivariate statistics or pattern recognition algorithms. Furthermore, it is possible to utilize additional variables, formed using a weighted combination of base variables, tuned for better discrimination for achieving better signal detection efficiency and purity.

3 Multivariate analysis and artificial neural networks

Data analysis techniques have evolved extensively in the current phase of high energy physics with powerful techniques available to efficiently extract signal information in background dominated data sample. Techniques using multivariate statistics or machine learning algorithms, such as Maximum Likelihood [21, 22], Fischer discriminants [23], Boosted Decision Trees [24] or Multilayer Perceptrons (MLP) [25, 26], to separate signal from background events have already been successfully
implemented to obtain various interesting physics results. In this work we are going to focus on the use of artificial neural networks (ANN), especially, MLP for the classification of prompt positron signature as signal event against delayed neutron capture and reactor γ-ray background events.

The multilayer perceptron (MLP), is the traditional form of artificial neural network [27]. It is a machine learning algorithm with a structure consisting of an input layer, one or more hidden layers, and an output layer. The MLP algorithm basically approximates a function mapping an \( n \)-dimensional input \( x \) to a \( m \)-dimensional output \( f \) in the real number space. The MLP layers are fully connected i.e. the output of each node is the weighted sum of the outputs of all nodes in the previous layer plus a bias term. These inputs are operated upon by a non-linear sigmoid function like \( \tanh \) at each node of a hidden layer [28]. Under certain assumptions, an MLP architecture with a single hidden layer can be shown to approximate any function to arbitrary precision given a sufficient number of hidden nodes [29, 30]. A supervised learning method [31] is traditionally used to determine the weights and biases used in an MLP. During this phase, the MLP is presented with data samples where both \( x \) and the corresponding output, \( f \), referred to as the ground truth, are known, for e.g. from simulations. The measure of the error between the output of the MLP and the ground truth, referred to as the ‘loss’, is computed. An algorithm called the back-propagation algorithm [32] calculates the gradient of this loss as a function of the weights and biases, which is then minimized by altering the weights and biases using the stochastic gradient descent method [33]. Repeated application of the above procedure is carried out till the errors are reduced to an acceptable level. However, in order to reduce the number of iterations to cut down on the computation time an alternative approach called the Broyden-Fletcher-Goldfarb-Shannon (BFGS) method can be utilized while adapting the synapse weights [34]. This method uses the second derivatives of the error function for adjusting the weights in each iteration. In this paper, we present the results of prompt signal and delayed background classification for ISMRAN detector by using the ‘Bayesian’ extension of MLP with the above BFGS method incorporated in it, referred to as ‘MLPBNN’ in the ROOT TMVA [35] package. The MLPBNN approach allows for increasing the complexity (more hidden units and/or more layers) of the architecture while simultaneously employing a regulator to avoid over-training. This is achieved through addition of another term in the network error function that effectively penalizes large weights, consequentely controlling the complexity of the model. For purposes of brevity in writing and also acknowledging the fact that MLPBNN is an extension of the more fundamental MLP algorithm, we will use only the term ‘MLP’ for the MLPBNN classifier here onwards. Similar work adopting the convolution visual network from the machine learning methods is used to describe neutrino interactions based on their topology [36].

4 Application of MLP to ISMRAN event classification

The MVA based classification, presented in this work, uses a simulated sample of 5M IBD events in ISMRAN detector. PS bars with energy deposit above the threshold : \( E_{\text{Th}}^{\text{bar}} = 0.2 \text{ MeV} \) and \( N_{\text{bars}} > 1 \) are used to reconstruct prompt and delayed events. As shown in Fig 2, identifying a reconstructed event as prompt or delayed events is the foremost concern in ISMRAN detector. The effectiveness of MLP as the classifier of choice for ISMRAN, is first demonstrated against the traditional ‘likelihood’ method. While the method of ‘cuts’ is a series of selections on the variables as attempted in our preliminary approach, the likelihood is a statistical method useful when looking
for signal from a limited data sample. Likelihood combines the probability density estimators for each variable and uses this product to classify the sample events. Although the process of both cuts and likelihood methods is transparent, the performance of these classifiers maybe hampered when there is significant correlation among the variables. Firstly, we compare the relative performances of likelihood and MLP classifiers for separating prompt positron events from delayed events of neutron capture on either Gd or H nucleus. The neutron capture delayed events on Gd comprises $\sim75\%$ of total neutron captures in ISMRAN detector [10] and the remaining 25% of the IBD produced neutron captures take place on hydrogen nuclei in the bulk of the scintillator volume. The prompt events are considered as the signal events while the delayed events are considered as background events. For both methods 100000 events are used for the classifier training. Another set of 100000 events, completely different from the training set, are simultaneously used for testing and evaluation purposes. In the case of MLP, additional inputs such as neuron type, the number of hidden layers, number of neurons in a hidden layer, testing iterations and frequency of the tests are provided to the classifier. The classifier response of likelihood and MLP methods are presented in Fig. 3 (a) and (b), respectively. The separation between the prompt signal and delayed background events for MLP is better than likelihood classifier. Figure 3 (c) shows the prompt signal efficiency vs delayed background rejection curve also called the ‘receiver operator characteristics’ - ROC for the two classifiers. The ROC curve shows better delayed background rejection in case of MLP, even for higher prompt signal efficiencies. These results make MLP classifier a better choice for ISMRAN IBD events out of the two compared classifier methods. It must be pointed out that the chosen MLP architecture in our study uses two hidden layers. The first hidden layer uses $N+5$ nodes while the second one uses $N$ nodes, where $N$ corresponds to the number of input variables. One of the input node apart from the input variables is the bias node, which is implicit in the MLP architecture. The two hidden layer configuration is found to have optimal performance for reasonable number of iterations in error minimization leading to less computational time.
5 Results from MLP classification

MLP response for prompt signal events and delayed background events for IBD interactions in ISMRAN:
The neutron capture events on Gd have a characteristic feature of energy deposits in PS bars and in the \(N_{\text{bars}}\) variable due to emission of cascade \(\gamma\)-rays from the de-excitation of Gd nucleus, which are expected to be more in number than that from a H-capture event as seen from equations 2, 3, and 4. The spread of the cascade \(\gamma\)-rays from Gd de-excitation eventually span multiple PS bars. Also, the sum energy of these energy deposits in PS bars is expected to fall in the energy ranges centered around 8 MeV region, for fully contained events. This characteristic feature of neutron capture delayed events on Gd, is expected to facilitate better classification of delayed background events when using MLP. A cut on the MLP classifier, using only sum energy and \(N_{\text{bars}}\) variable, which selects \(\sim 90\%\) of prompt signal events from the sample can only provide \(\sim 65\%\) rejection of the delayed background events, as shown in Fig. 3(c). Further improvements in the existing framework are therefore needed to increase the prompt signal efficiency of the classifier response. In order to achieve this, we introduce a new variable constructed using the weighted individual bar energy deposits formulated as: 

\[ D_k = (E_{\text{total}})^{-k} \times (\sum w_i (E_i)^k) \]

where \(E_{\text{total}}\) is the total sum energy, \(E_i\) is the individual PS bar energy deposit, \(k\) is a real number, and the weight factor is defined as 

\[ w_i = E_i / E_{\text{total}} \].

In case of \(D_k\), the choice of exponent \(k\) as 2.5 is observed to provide better discrimination ability compared to other values of \(k\). The formulation of the variable \(D_k\) is such that it makes use of the difference in the energy deposition profiles of the prompt positron signal events and delayed neutron background events and consequently enhances their separation as seen in Fig. 4(a). Figure 4(b) shows better separation in the MLP classifier response, after inclusion of \(D_k\) and Fig. 4(c) shows the comparison of ROC curves with and without inclusion of \(D_k\) for prompt signal efficiency and delayed background rejection. It can be seen that there is a significant improvement in delayed background rejection for a given prompt signal efficiency with the inclusion of \(D_k\) in the MLP classifier. All the MLP classifier results presented, here onwards, are with the

![Figure 4](image-url)
inclusion of $D_h$ along with sum energy and $N_{\text{bars}}$ variables.

**MLP response for prompt signal events and neutron capture on Gd and H background events separately in ISMRAN:**

Majority of the neutron capture events ($\sim 75\%$) occur on Gd, the remaining 25\% of the IBD produced neutron captures take place on hydrogen nuclei in the bulk of the scintillator volume. A cascade $\gamma$-ray is produced in Gd capture events, while a mono-energetic $\gamma$-ray of 2.2 MeV released from a neutron capture on H. These characteristics of the delayed background events would behave differently while training the MLP classifier. Hence, it is important to evaluate the MLP classifier response to these two set of delayed background event and there corresponding background rejection efficiencies. This is addressed within the MLP framework by individually studying the delayed background events from neutron capture on Gd and H. Figure 5 (a) and (b) show the MLP response and classification for neutron capture on Gd and H, respectively. The separation in the classifier response is good in both the Gd and H capture events from the prompt single events. Figure 5 (c) shows the delayed background event rejection for Gd and H capture events as a function of prompt signal efficiencies. It can be seen that the rejection of delayed backgrounds using MLP is quite effective in both Gd and H capture events keeping reasonable prompt signal efficiencies.

**MLP response for prompt signal events and reactor $\gamma$-ray background events in ISMRAN:**

The experimental setup of ISMRAN detector inside reactor hall poses a hostile environment for anti-neutrino detection due to the ambient reactor $\gamma$-ray backgrounds. These $\gamma$-rays are emanating mostly from the neutron capture on the surrounding materials present in the reactor hall, namely the stainless steel structures and beam dumps used in reactor operations or for various neutron scattering experiments. We have taken a reference $\gamma$-ray spectrum for such events from the PROSPECT experimental site selection studies [37], particularly at the NBSR site where the $\gamma$-ray activity is quite intense and varied in energy. This allows for the test of the MLP classifier response in a more realistic reactor $\gamma$-ray background. The above reactor background $\gamma$-ray distribution is used as an input in our GEANT4 simulations and events are recorded for a shielded ISMRAN detector geometry. These events are considered as the background events, and the MLP classification is
Figure 6. Panel (a) MLP classifier response for prompt signal from positron and reactor γ-ray backgrounds. Panel (b) ROC curve for the prompt signal efficiency and reactor γ-ray background rejection.

Figure 7. Prompt signal efficiency, purity and product of efficiency and purity for MLP as a function of different selection cut values on the MLP output.

Performance evaluation of MLP using a combined background of Gd and H neutron capture events in ISMRAN:

To test the performance of MLP classifier in real scenarios, we prepare a sample of 100000 events of prompt signal with a mixed sample of Gd and H neutron capture delayed background events. This inclusion of H neutron capture events as potential delayed events is one of the advantages of using the MLP method over the cut based selection which rejected such events and led to reduced $\bar{\nu}_e$ signal detection efficiencies. The MLP performance parameters such as prompt signal efficiency,
Table 2. Signal efficiency, purity and background rejection performance with optimized cuts on MLP classifier.

| MLP cut value | Signal Efficiency (%) | Signal Purity (%) | Background rejection (%) |
|---------------|-----------------------|-------------------|--------------------------|
| s/√(s + b)    | 0.37                  | 91.5              | 77.3                     |
| s/√b          | 0.88                  | 56.4              | 93.5                     |

Figure 8. Panel(a) : Prompt sum energy distribution for true input, events classified with MLP and from a cut based analysis. Panel(b) shows the delayed background events which are misidentified as prompt signal events using MLP classifier and cut based analysis.

purity and their product are calculated as a function of different selection of cut values on the MLP response. Figure 7 shows the relative behavior of these three parameters for different selection cuts on the MLP classifier in percentages. In the region of MLP response values from 0.2 to 0.6 the product of signal efficiency and purity is close to 70\%. The performance of the MLP classifier is obtained in terms of figures of merit (FOM), s/√(s + b) and s/√b, where s and b define the prompt signal and delayed background events, respectively, in the sample. The quantity s/√(s + b) can be used to maximize the efficiency of the prompt signal events with the classifier response and s/√b is used for obtaining the maximum purity of the prompt signal in presence of delayed background. The table 2 shows the signal efficiency, signal purity and background rejection for selection cut values which maximizes the s/√(s + b) and s/√b. The efficiency value of 91.5\%, as obtained for maximally efficient classification of prompt signal, is a significant gain over the earlier cut based efficiency of 69\% (see table 1). The maximum purity of the prompt signal events can reach ~93\% at the MLP selection cut of 0.88 with an efficiency of ~56\% for the prompt signal events. The optimal selection of cut value on the MLP response may be selected in these ranges to achieve a moderate prompt signal efficiency with a reasonable prompt signal purity. To show the performance of the MLP classifier on selecting the prompt signal events, we apply the classifier response on the 100000 independent IBD events. All the events which satisfies the classifier cut selection above 0.37 are chosen as prompt signal events. Figure 8 (a) shows the prompt sum energy distribution of input events (shown in black), after application of the MLP classifier response on the input events (shown in red dashed) and that from a simple cut based analysis choosing ‘loose’ cuts on prompt signal, as in table 1 (shown in dashed dot blue). It can be seen that using MLP a significant improvement in
the efficiency and spectral shape of prompt energy distribution is obtained as compared to a simple cut based analysis results. Figure 8 (b) shows the delayed background events distribution for MLP and cut based analysis which are filtered as prompt signal events with the same selection criteria which were implemented for prompt signal selection. It can be seen that the MLP based classifier are filtering less number of events which can be marked as prompt signal events as compared to that from a cut based analysis. Also more number of background events, at around 2MeV from neutron capture on H, are misidentified as prompt signal events in case of cut based analysis as compared with MLP classifier. Overall the purity of the prompt signal events is higher in case of MLP classifier as compared to a simple cut based analysis.

6 Conclusions and Outlook

Machine learning technique using multilayer perceptron algorithm is applied to discriminate prompt and delayed events arising from IBD interactions in the ISMRAN detector. Using simulations, it has been shown that this technique provides an excellent separation of prompt signal events from other event classes such as the delayed neutron capture on Gd, H and background γ-rays from reactor. The performance of MLP classifier is better as compared to the statistical methods of cut based or likelihood based classification. An addition of new variable, \(D_k\), obtained from weighted energy deposits in bars further improves the response of MLP classifier. Prompt signal efficiencies close to \(\sim 91\%\) has been obtained while rejecting \(\sim 73\%\) of the delayed background in ISMRAN detector. In future, MLP classifier may be used to discriminate other source of backgrounds which include cosmogenic muon spallation and neutron induced backgrounds for obtaining better anti-neutrino detection efficiency in ISMRAN.

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