Machine learning approaches to automate the calibration process for γ-ray detectors

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Introduction

Machine learning (ML) techniques enable systems to autonomously recognize patterns and relationships within large datasets, allowing them to make predictions when presented with new data. In recent years, ML has gained considerable attention in nuclear physics, where it has been utilised for various applications [1], including prediction of nuclear masses, modeling nuclear reactions, constraining equation of state for neutron stars and in nuclear experiments for charged particle tracking, recoil identification, and γ spectroscopy [2, 3, 4].

In modern γ-ray spectroscopy experiments, a large number of detectors are used to ensure better efficiency. Calibration of γ-ray detectors involves obtaining calibration parameters, which relate a specific channel number to a particular energy from known energy sources. However, these calibration parameters do not remain constant throughout the experiment due to drift in the gain of the detectors. Consequently, one needs to perform calibration for all the reaction data files. The manual calibration procedure for a large number of detectors is a very time-consuming and tedious process. Therefore, we have explored the potential of various machine-learning approaches to automate the calibration process.

ML Models and Training

We have utilized various ML regression models, with the most notable being K-Nearest Neighbour (KNN), Random Forest (RF), and Gradient Boosting (GB), for our task. KNN predicts the energy by calculating the mean energy value of the nearest k neighbours in terms of the channel number. RF creates multiple training datasets from the given data, on which each decision tree can be trained to improve the accuracy and robustness. GB builds models sequentially, with each new model correcting the errors of the previous one, to make accurate predictions.

To test the applicability of ML approaches for the calibration procedure, we have utilized the standard ^{152}Eu source data. This data was collected with the Indian National Gamma Array (INGA), comprising of 13 clover HPGe detectors, at Inter University Accelerator Centre (IUAC), New Delhi. A total of 23 root files were available, out of which spectra from 17 root files were used to train the ML models, while the data from the remaining 6 files were used for testing. The reasoning behind this partition is based on the estimated average RMSE, which is discussed in the next section.

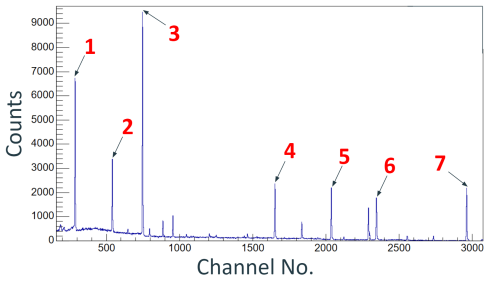

FIG. 1: A histogram displaying the ^{152}Eu source spectrum with the peaks used for calibration highlighted.

Fig. 1 illustrates a representative ^{152}Eu source spectrum for one of the detectors. The channel numbers corresponding to the source energies viz. 121.8, 244.7, 344.3, 778.9, 964.1,

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1112.1, and 1408.0 keV were determined using the peak prominence method. After obtaining the channel numbers of these seven peaks, we determine the parameters that relate those channel numbers to the known energy values of the corresponding peaks. The relationship between channel number and energy is assumed to be of the following form:-

$$E = a_0 + a_1\sqrt{x} + a_2 x + a_3 x^2, \qquad (1)$$

where E is the energy of the γ ray, x is the channel number, and a_0, a_1, a_2, a_3 are the calibration coefficients.

Results and Discussion

We have tested different ML models on the data from 6 files, which consisted of a total of 294 spectra. The validity of different machine learning models was evaluated by determining the average root mean squared error (RMSE). Out of the three above mentioned models, KNN (with weighted distance and k=3) demonstrated superior performance (see Table I and II) by predicting the energy peaks of a given channel number resulting in the lowest RMSE.

ML model	Average RMSE
KNN	0.42
RF	1.48
GB	2.54

TABLE I: Comparison of the average RMSE using three ML models.

Range	KNN	RF	GB
RMSE < 0.5	89.46	47.62	11.56
$0.5 <$ RMSE < 1	8.5	23.13	27.21
RMSE > 1	2.04	29.25	61.22

TABLE II: Distribution of RMSE (in %) using the three ML models for testing data.

Furthermore, the KNN model's performance is assessed by varying the training dataset size and monitoring its effect on the average RMSE (see Table III). The least average value of RMSE is obtained when data from 17 files (i.e. 73.9 % of the dataset) were used for training and the 6 remaining files (i.e. 26.1 % of the dataset) were used for testing.

Number of training files	Average RMSE
14	0.72
15	0.70
16	0.50
17	0.42
18	0.45
19	0.53
20	0.66

TABLE III: Variation of average RMSE with the number of training files for KNN.

In order to improve the results, deep learning models such as convolutional neural network (CNN), artificial neural network (ANN) etc. will be utilised in the future as these are particularly useful for extracting peak features and learning patterns in complex reaction data. Furthermore, it is interesting to note that the automated calibration of γ-ray detectors can be utilized for real-time anomaly detection in the performance of detector or associated electronics by employing proper data preprocessing and peak feature selection. As a result, suitable actions in that regard will also be taken.

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