Neural Network-Based Analysis of Nuclear Pulse Signals[*]

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Abstract

In response to the requirements for high-precision, low-cost, and portable spectrometric analysis in nuclear radiation detection, this paper presents a neural network approach for nuclear signal processing, enabling a direct nonlinear relationship between sampled nuclear pulse signals and their energy labels. This method leverages a deep neural network model to automatically extract features and predict energy, effectively simplifying the traditional workflow involving denoising, baseline correction, digital pulse shaping, and peak detection. A systematic evaluation of the model' s performance in terms of main peak position, energy resolution, and spectral linearity was conducted through comparative experiments on ^{137}Cs and uranium ore samples at sampling rates of 500~MSPS, 50~MSPS and 20~MSPS. The results demonstrate that the neural network model achieves comparable spectrum reconstruction performance to the traditional PHA method at both high and low sampling rates, and preserves good resolution and linearity even with significant reduction in sampling points. Furthermore, it is found that the quality of the energy labels directly determines the network output, underscoring the importance of accurate labeling for improved spectrum reconstruction accuracy. This approach significantly streamlines the signal analysis procedure and offers novel insights and basis for developing compact, embedded, and intelligent nuclear detection systems.

Full Text

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In response to the requirements for high-precision, low-cost, and portable spectrometric analysis in nuclear radiation detection, this paper presents a neural network approach for nuclear signal processing, enabling a direct nonlinear relationship between sampled nuclear pulse signals and their energy labels. This method leverages a deep neural network model to automatically extract features and predict energy, effectively simplifying the traditional workflow involving denoising, baseline correction, digital pulse shaping, and peak detection.

A systematic evaluation of the model' s performance in terms of main peak position, energy resolution, and spectral linearity was conducted through comparative experiments on ^{137}Cs and uranium ore samples at sampling rates of 500 MSPS, 50 MSPS and 20 MSPS. The results demonstrate that the neural network model achieves comparable spectrum reconstruction performance to the traditional PHA method at both high and low sampling rates, and preserves good resolution and linearity even with significant reduction in sampling points. Furthermore, it is found that the quality of the energy labels directly determines the network output, underscoring the importance of accurate labeling for improved spectrum reconstruction accuracy. This approach significantly streamlines the signal analysis procedure and offers novel insights and basis for developing compact, embedded, and intelligent nuclear detection systems.

Keywords: Neural network; Nuclear signal processing; Digital multichannel; Low sampling rate

I. INTRODUCTION

Nuclear radiation detection techniques are of significant value in nuclear energy production and safety, environmental monitoring, and medical diagnostics. High-precision energy spectrum analysis forms the basis for improved material identification, radioactive contamination discrimination, and enhanced performance in safety warning systems. With advances in high-speed ADCs and programmable hardware, nuclear spectrometry has increasingly shifted from conventional analog shaping chains to digital pulse processing (DPP) and full waveform analysis. Recent studies and comprehensive reviews provide systematic overviews of DPP applications in nuclear spectroscopy [1], while modern prototypes based on fast ADCs and DSPs have demonstrated the superior potential of full waveform peak extraction over traditional analog shaping in terms of energy resolution and linearity [2, 3]. At the system level, digital acquisition solutions utilizing the Pixie-16 module, as well as review articles in *Nuclear Science and Techniques*, have confirmed the comprehensive advantages of digitalization—such as high count rate capability, low dead time, and intelligent signal processing—through practical applications with gamma-ray arrays and diverse detector systems [4].

Digital multi-channel analyzers (MCAs) currently constitute the mainstream instruments for nuclear spectrometry, with pulse height analysis (PHA) forming the principal analytical technique. To enhance energy labeling, Li *et al.* introduced pulse area analysis (PAA), which exhibits superior spectral resolution relative to conventional PHA, particularly at high count rates and short shaping time constants [5]. Wang *et al.* proposed pulse fitting analysis (PFA), leveraging the fitting and integration of double-exponential falling edges; this method achieves resolution and linearity on embedded SoC platforms comparable to or surpassing those of commercial MCAs [6].

In the research field of nuclear signal digital shaping and filtering, research

has focused on the construction of universal domain models and experimental analysis. These models incorporate Sallen-Key digital filters [7], CR-RCm digital filters [12], and cascaded digital Gaussian filtering architectures [9-11]. By comparing the results of different shaping times and integration orders, quantitative relationships between energy resolution and count rate have been clarified [8, 13]. Additionally, for fast channels and baseline restoration, symmetric zero-area trapezoidal (SZA) [14] and "bald" flat-top (SZAB) shaping [15], as well as real-time cusp-like shaping algorithms [16], have been proposed. These methods effectively suppress baseline drift and false peaks, enhancing trigger stability and pile-up rejection under high count rate conditions.

With the expansion of nuclear signal processing from laboratory settings to practical applications in field monitoring, industrial in-line inspection, and medical security, systems

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contend with stringent requirements for limited hardware resources, device miniaturization, and reduced power consumption. At high count rates, pile-up and baseline restoration emerge as major factors impacting spectral quality. To address these challenges, template-matching methods [18], iterative deconvolution techniques [17], and partial waveform-based pile-up identification [19] have been introduced to optimize throughput and energy resolution. Concurrently, engineering advances such as adaptive triggering with dynamic pulse width estimation [20, 21], and digital system implementations for $2\pi\alpha/2\pi\beta$ measurements [22], n/γ discrimination [23, 25], and high-speed data acquisition [24] have further enabled robust operation in complex environments.

On the algorithmic front, conventional workflows relying on analytical filters are increasingly challenged by severe pile-up and complex noise. This has fostered the adoption of data-driven and neural network techniques. Genetic algorithms [26] and LSTM-based parameter regression [27] have been explored to address these limitations. Furthermore, deep learning approaches, such as U-net and regression-based denoising, have been applied to pile-up separation tasks [28, 29]. Novel implementations, including MLP-DPSA [30] and architectures combining multimodal fusion [32], convolutional autoencoders [33], and ANN-based models [34, 35], have demonstrated considerable promise in pulse shape discrimination and spectrum reconstruction.

From the perspective of system design and implementation, advances such as recursive approximate Gaussian filtering [36], rising edge recovery modeling and pole-zero cancellation [31, 37], and Lagrange interpolation [38] have provided

viable approaches for resource-constrained environments. Moreover, single-chip ARM Cortex-M7 spectrometer solutions [39] and time-sharing multi-channel analysis [40] have been developed to achieve low detection thresholds and real-time multi-channel processing.

In summary, advancements in digital shaping, pile-up recognition, neural network-driven parameter estimation, and embedded digital spectrometers share the overarching aim of improving spectral quality and system operability. Nevertheless, simultaneous optimization of processing speed, algorithm adaptability, and hardware integration remains difficult. Traditional analytical filtering and rule-based methodologies continue to encounter bottlenecks in balancing high-precision spectral reconstruction with throughput and power efficiency.

This study presents a neural network–based nuclear signal processing approach. By leveraging high-quality energy labels generated at high sampling rates, supervised learning is used to train a neural network that directly maps sampled signals to energy labels. The reconstruction capabilities of the method are systematically evaluated under low sampling rate conditions. The article details the workflow for signal preprocessing, dataset construction, network architecture design, and sensitivity analysis, offering innovative engineering solutions for miniaturized and embedded nuclear spectrometry systems.

II. THEORY AND METHODOLOGY

A. Neural Network Analysis Method

To enable automated analysis of nuclear pulse signal energy, this study applies neural network techniques to the spectrum acquisition stage, thereby streamlining the traditionally complex signal analysis workflow. This methodology is closely aligned with recent advances in deep learning for pulse height estimation, pile-up discrimination, and parameter regression [28–30]. An overview of the complete methodological workflow is illustrated in Figure 1.

In contrast to conventional analytical methods—which require sequential steps such as denoising, baseline estimation, pulse shaping, and peak extraction to determine pulse amplitude—the neural network model can directly learn the mapping between raw signals and energy using training samples, thereby streamlining the process from signal acquisition to energy output.

1. ***Pulse Signal Modeling and Standardization*** Sampled signals are subjected to preprocessing procedures—including denoising and baseline correction—and subsequently normalized to serve as neural network inputs. The signals are modeled using a conventional double exponential form, which aligns with pulse modeling approaches found in studies of equivalent front-end RC networks and rising edge recovery [37]:

$$x(n) = \begin{cases} b, & nT \le t_0 \\ A\left(e^{-\frac{nT-t_0}{\tau_d}} - e^{-\frac{nT-t_0}{\tau_r}}\right) + b, & nT \ge t_0 \end{cases} \tag{1}$$

Here, n denotes the nth sampling point, A represents the amplitude, τ_d and τ_r correspond to the decay and rise time constants, respectively, and b is the baseline. For real signals, the effects of noise and baseline drift must also be considered:

$$x'(n) = x_{\text{signal}}(n) + x_{\text{noise}}(n) \tag{2}$$

2. ***Neural Network Forward Propagation*** The standardized sampled vector is fed into the neural network for energy prediction. Taking a multilayer feedforward neural network as an example, the inter-layer computations are as follows:

The input to the jth neuron in the lth layer is given by:

$$z_j^{(l)} = \sum_i w_{ij}^{(l)} a_i^{(l-1)} + b_j^{(l)} \tag{3}$$

where $w_{ij}^{(l)}$ refers to the weight, $b_j^{(l)}$ is the bias term, and $a_i^{(l-1)}$ is the output from the preceding layer.

The activation function is defined as follows (here, e.g., ReLU is used):

Fig. 1. Neural network analysis flow for nuclear pulse signals.

$$a_j^{(l)} = \max\left(0, z_j^{(l)}\right) \tag{4}$$

The output layer produces the regression output for energy prediction. Denote the final neural network output as

$$I_{\text{pred}} = F\left(x'(n)\right) \tag{5}$$

where $F(\cdot)$ denotes the neural network function.

3. Neural Network Training and Backpropagation The neural network parameters are optimized by minimizing a loss function. In this study, the mean squared error (MSE) loss is employed:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(I_{\text{pred},i} - I_{\text{true},i}\right)^2 \tag{6}$$

where N denotes the total number of samples, and $I_{\text{true},i}$ is the reference energy value.

During backpropagation, the derivatives of the loss function with respect to the weights are calculated, and the parameters are updated using the gradient descent method:

$$w_{ij} \leftarrow w_{ij} - \eta \frac{\partial \text{MSE}}{\partial w_{ij}} \tag{7}$$

where η denotes the learning rate. This iteration continues until the loss converges.

4. Inference and Energy Prediction After training, newly acquired sampled pulse signals are standardized and then directly fed into the neural network, which yields energy predictions through multiple layers of weighting and activation. If output standardization was performed during training, inverse standardization can be applied during the inference phase to restore the actual energy or amplitude according to the following formula:

$$I_{\text{pred}} = I_{\text{pred,norm}} \times \sigma + \mu \tag{8}$$

where $I_{\text{pred,norm}}$ denotes the standardized prediction output from the neural network; μ and σ represent the mean and standard deviation of the training set labels, respectively.

B. Methods for Energy Label Acquisition

Training neural network models generally requires high-quality supervised labels. In the field of nuclear pulse signal analysis, the commonly used methods for energy label acquisition include pulse height analysis (PHA), pulse area analysis (PAA), and pulse integration analysis (PIA). Essentially, all these methods map the energy to different feature quantities.

In the PHA method, the maximum amplitude of the signal is used as the energy parameter. The mapping relationship is given by Equation (9):

$$P_H = V_{\text{out}}(t) = \frac{Q}{C_f} e^{-\frac{t}{\tau_d}} \tag{9}$$

where Q denotes the charge carried by the detector output signal, C_f is the feedback capacitance of the preamplifier, and τ_d represents the decay time constant of the nuclear pulse. This method is easy to implement and well-suited for digital processing, but it is sensitive to high-frequency noise and sampling rate. Especially under conditions of high count rates or signal pile-up, its energy resolution and accuracy are limited.

Fig. 2. Photograph of the experimental measurement setup. Visible labels: $LaBr_3$:Ce scintillator detector; high-voltage power supply; CAEN DT5730S; ^{137}Cs source; real-time spectrum display software.

Figure 1: Fig. 2. Photograph of the experimental measurement setup. Visible labels: $LaBr_3$:Ce scintillator detector; high-voltage power supply; CAEN DT5730S; ^{137}Cs source; real-time spectrum display software.

In the PAA method, the energy is represented by the integrated area under the signal, as given by Equation (10):

$$P_A = \frac{3\tau e^4}{32} \cdot P_H \tag{10}$$

Compared with PHA, PAA exhibits enhanced noise immunity and offers the potential for improved resolution. However, it demands higher ADC sampling precision and is more sensitive to the pulse waveform shape, making its practical implementation highly dependent on hardware performance [5].

The pulse integration analysis (PIA) method reconstructs the impulse response function by applying nonlinear fitting

to the falling edge of the pulse, and calculates the energy via integration. The mapping relationship is given by Equation (11):

$$Q = \frac{1}{R_f} \int_{t_0}^{\infty} [h(t) - b]dt \tag{11}$$

where R_f denotes the feedback resistance in the preamplifier, b is the signal baseline, t_0 denotes the event time of the nuclear pulse, and $h(t)$ is the impulse response function obtained via fitting. This approach delivers theoretically high accuracy and robust baseline stability, and has been applied in multiple front-end and digital shaping frameworks for mitigating baseline drift and ballistic deficit [6, 12, 31]. Nevertheless, the computational complexity inherent in the fitting and integration stages impedes real-time performance and poses significant challenges for hardware implementation.

Fig. 2. Photograph of the experimental measurement setup.

III. EXPERIMENT

A. Experimental Conditions and Data Collection

For this experiment, the samples consisted of a ^{137}Cs monoenergetic gamma-ray source and uranium ore powders with uranium grades of 8739 ppm and 15445 ppm. All radioactive sources were measured using a 2×2 inch $LaBr_3$ scintillation detector, with signals acquired by a CAEN DT5730S multi-channel

digitizer. The DT5730S features a 14-bit, 500 MSPS (mega-samples per second) high-speed analog-to-digital converter, allowing for high-precision acquisition and storage of each pulse waveform. With integrated Digital Pulse Processing (DPP) firmware supporting algorithms such as pulse height analysis (PHA), the DT5730S enables the synchronous output of energy labels and real-time spectral data for each pulse, thus providing standard references critical for neural network training and model evaluation. The experimental platform is further complemented by dedicated host PC software, which facilitates raw waveform storage and real-time display of energy spectra. The overall architecture and signal flow of the system are illustrated in Figure 2, encompassing key components including the radiation source, detector, digitizer, and real-time energy spectrum display.

All samples were continuously recorded at room temperature for 3 minutes, during which all valid raw waveforms and their corresponding PHA energy labels were comprehensively collected. As a result, these raw data constituted the standardized dataset used for all neural network experiment groups. Specific experimental variables—including sampling rate, downsampling configurations, and energy labeling schemes—will be detailed in Section 4 in conjunction with the corresponding experimental designs.

B. Neural Network Architecture and Training Process

To reconstruct the energy of nuclear pulse waveforms, a neural network model featuring a fully connected architecture was developed in this study. The standard architecture comprises an input layer—whose number of nodes corresponds to the number of sampling points—followed by two fully connected hidden layers with 16 nodes each, both employing the ReLU activation function, and a single-node output layer. Prior to training, all input and output data were standardized by mean-variance normalization. The training samples were primarily sourced from data collected using the ^{137}Cs source, with energy labels provided by both the digitizer' s PHA algorithm and results obtained via the bi-exponential fitting method.

The dataset was randomly split into training and testing sets in a 7:3 ratio to improve the model' s generalization ability. During training, mean squared error (MSE) was employed as the loss function, while the Adam optimizer was used in conjunction with adaptive learning rate adjustment and gradient clipping to ensure training stability and convergence. Training was performed with GPU acceleration, and all model parameters were saved following the completion of training.

Neural network models were developed for each experimental scheme at sampling rates of 500 MSPS, 50 MSPS, and 20 MSPS, corresponding to pulse signal lengths of 648, 65, and 26, respectively. All other aspects of the network architecture and training process were kept identical. All models were trained on data collected from the Cs source. Details regarding the energy labeling schemes

Fig. 3. Neural network model architecture.

Figure 2: Fig. 3. Neural network model architecture.

and other experimental specifics will be provided in Section 4. The architecture of the network model is illustrated in Figure 3.

IV. RESULTS AND ANALYSIS

A. Neural Network and PHA Performance at 500 MSPS

To assess the neural network model' s capability to reconstruct pulse amplitudes from different radiation sources, experiments were conducted using pulse signals collected at

Visible labels in the diagram: Input layer (N node); Hidden layer 1 (16 neuron nodes); Hidden layer 2 (16 neuron nodes); Linear output layer (1 neuron nodes).

Fig. 3. Neural network model architecture.

500 MSPS. The evaluation included a single-energy peak Cs source and two groups of uranium ore powder samples (8739 ppm and 15,445 ppm). The model was trained on Cs source samples, and its reconstruction performance was assessed on both the Cs source test set and the two uranium ore powder sample groups that were excluded from training. Using energy labels generated by the digitizer' s built-in PHA algorithm as a reference, the neural network model and the PHA method were systematically compared in terms of main peak position, energy resolution, and multi-peak spectral linearity, thereby verifying the model' s accuracy and effectiveness.

The energy spectra reconstructed by the PHA method and the neural network model for each of the three radiation sources are shown in Figure 4. For the 662 keV main peak of the Cs source, the PHA method yielded a peak position of 1082 channels and an energy resolution of 4.90%, while the neural network model achieved 1079 channels and 4.82%. For the 609 keV main peak of the uranium ore powder samples (8739 ppm and 15,445 ppm), the PHA method yielded peak positions and energy resolutions of 996/4.62% and 987/4.46%, respectively, whereas the neural network model achieved 990/4.55% and 994/4.33%, respectively. These results indicate that differences between the two methods in main peak position and energy resolution are negligible, demonstrating excellent consistency.

Further analysis of multi-peak spectral linearity (Figure 5) shows that, for uranium ore powder samples with concentrations of 8739 ppm and 15,445 ppm, the PHA method yielded R^2 values of 1 and 0.99998 for the main characteristic peaks (609 keV, 1120 keV, 1764 keV), respectively, while the neural network predictions produced R^2 values of 1 and 0.99999, respectively. Overall, the neural network model demonstrated results highly comparable to the PHA method in

Fig. 4. Comparison of energy spectra reconstructed by the PHA method and the neural network at 500 MSPS.

Figure 3: Fig. 4. Comparison of energy spectra reconstructed by the PHA method and the neural network at 500 MSPS.

Fig. 5. Linear fitting of main characteristic peaks in uranium ore powder samples.

Figure 4: Fig. 5. Linear fitting of main characteristic peaks in uranium ore powder samples.

both peak position fitting and spectral linearity.

In conclusion, the neural network model achieved high-precision energy reconstruction for pulse signals from different radiation sources at 500 MSPS, with main peak resolution and multi-peak linearity comparable to the traditional PHA method, thereby confirming both the accuracy and reliability of its outputs.

Visible panel headings: Standard PHA Method (Label); BP Neural Network @ 500 Msps; Cs-137 Source; U Sample (8739); U Sample (15445).

Fig. 4. Comparison of energy spectra reconstructed by the PHA method and the neural network at 500 MSPS.

Visible panel headings: Standard PHA Method (Label); BP Neural Network @ 500 Msps; U Sample (8739); U Sample (15445).

Fig. 5. Linear fitting of main characteristic peaks in uranium ore powder samples.

B. Neural Network at Different Sampling Rates

To further examine the impact of input sampling rate on neural network spectrum reconstruction performance, the original 500 MSPS sampled signals were downsampled to 50 MSPS and 20 MSPS, with energy labels provided by the PHA method kept constant. Separate neural networks were trained using Cs source data at each sampling rate. Model inference was subsequently evaluated on the corresponding Cs source

test sets and two groups of uranium ore powder samples not included during training. A systematic comparison of main peak energy resolution and multi-peak spectral linearity was conducted to assess the effect of sampling rate changes on model performance.

Figure 6 shows neural network energy spectrum reconstruction for three radiation sources at different sampling rates. At 50 MSPS, the 662 keV main peak of the Cs source exhibited a peak position of 1072 channels and an energy resolution of 4.76%. For the 609 keV main peak of uranium ore powder samples

Energy spectra reconstructed by the neural network at different sampling rates. Panels compare BP Neural Network @ 50 Msps and BP Neural Network @ 20 Msps for Cs-137 Source, U Sample (8739), and U Sample (15445).

Figure 5: Energy spectra reconstructed by the neural network at different sampling rates. Panels compare BP Neural Network @ 50 Msps and BP Neural Network @ 20 Msps for Cs-137 Source, U Sample (8739), and U Sample (15445).

Linear fitting of main characteristic peaks in uranium ore powder samples at different sampling rates. Panels compare BP Neural Network @ 50 Msps and BP Neural Network @ 20 Msps for U Sample (8739) and U Sample (15445).

Figure 6: Linear fitting of main characteristic peaks in uranium ore powder samples at different sampling rates. Panels compare BP Neural Network @ 50 Msps and BP Neural Network @ 20 Msps for U Sample (8739) and U Sample (15445).

with concentrations of 8739 ppm and 15,445 ppm, the corresponding values were 997/4.31% and 996/4.32%, respectively. At 20 MSPS, the Cs source main peak appeared at 1075 channels with an energy resolution of 4.56%, while the uranium ore powder main peaks were 985/4.97% and 989/4.65%, respectively. These results indicate that both the main peak position and energy resolution at different sampling rates are comparable to those at the high sampling rate of 500 MSPS, with minimal overall differences.

Fig. 6. Energy spectra reconstructed by the neural network at different sampling rates.

Further analysis of spectral linearity (Figure 7) shows that at 50 MSPS, the R^2 values of the main characteristic peaks for the 8739 ppm and 15,445 ppm uranium ore powder samples were 1 and 0.99999, respectively. At 20 MSPS, the R^2 values were 0.99994 and 1, respectively. Multi-peak spectral linearity was well maintained across all sampling rates.

Fig. 7. Linear fitting of main characteristic peaks in uranium ore powder samples at different sampling rates.

Compared with the high sampling rate results, reducing the neural network input sampling rate from 500 MSPS to 50 MSPS or even 20 MSPS resulted in almost no discernible decrease in main peak position, energy resolution, or multi-peak spectral linearity, indicating strong model robustness. These findings suggest that even when the input information is significantly compressed, the neural network consistently achieves stable and accurate energy spectrum reconstruction, demonstrating substantial potential for real-world applications under diverse acquisition conditions.

C. Neural Network Spectrum Reconstruction with Different Labels

To evaluate the influence of label quality on neural network spectrum reconstruction performance, a bi-exponential fitting method was used to generate energy labels for the Cs source and two uranium ore powder samples (8739 ppm and 15,445 ppm). The network was then trained on the labeled Cs source data. After training, the model was evaluated on both the Cs source test set and the two uranium ore powder samples not used during training. Systematic comparisons of main peak position, energy resolution, and spectral linearity were undertaken to assess the network' s ability to fit different label types, as well as to analyze the impact and dominant role of labeling algorithms on the final spectrum reconstruction performance.

Figure 8 compares the results of bi-exponential fitting labels and neural network reconstruction. For the Cs source 662 keV peak, bi-exponential fitting yielded 1081 channels/6.63%, while the neural network gave 1073 channels/6.90%. For the 609 keV peaks of the uranium ore powders (8739 ppm and 15,445 ppm), the bi-exponential fitting results were 991/5.35% and 991/5.45%, respectively, and the neural network produced 987/5.88% and 990/5.76%.

The neural network showed excellent agreement with the bi-exponential fitting labels in reconstructing both the main peak position and energy resolution.

Figure panel headings: **Standard PIA Method (Label)**; **BP Neural Network @ 500 Msps**.
Rows: **Cs-137 Source**; **U Sample (8739)**; **U Sample (15445)**.

Fig. 8. Comparison of energy spectra obtained from bi-exponential fitting labels and neural network reconstruction.

Further analysis of energy spectrum linearity (Figure 9) shows that, using bi-exponential labels, the fitted R^2 values for the three main characteristic peaks of the 8739 ppm and 15,445 ppm samples were 0.99629 and 0.99757, respectively. For neural network inference, the R^2 values were 0.99988 and 0.99999, respectively. These results indicate high linearity in both cases, demonstrating that the model can effectively capture the spectral distribution characteristics encoded by the labels.

To quantitatively compare spectral performance across different labeling and reconstruction approaches, Table 1 summarizes the main peak positions and energy resolutions of the three radioactive sources corresponding to PHA labels, bi-exponential fitting labels, and the outputs of neural network models trained on each label type.

In conclusion, the neural network model is capable of accurately learning and reproducing the spectral features and resolution levels associated with different bi-exponential fitting labels. Combined with the high-precision reconstruction performance observed at 500 MSPS, these results demonstrate that the resolution and linearity of the energy labels directly determine the model' s

ultimate performance; while the neural network can precisely reconstruct label features, its output cannot exceed the inherent quality of the labels. Therefore, high-quality energy labels are essential for improving the performance of neural network-based spectral reconstruction.

Figure panel headings: **Standard PIA Method (Label)**; **BP Neural Network @ 500 Msps**.
Rows: **U Sample (8739)**; **U Sample (15445)**.

Fig. 9. Linear fitting of main peaks for bi-exponential labels and neural network.

Table 1. Comparison of main peak channel and resolution for different labels and NN outputs

Sample	Method / Label	Peak Channel	Energy Resolution (%)
Cs-137 (662 keV)	PHA	1082	4.90
	NN (PHA)	1079	4.82
	Double-exponential	1081	6.63
	NN (Double-exponential)	1073	6.90
Uranium ore 8739 ppm (609 keV)	PHA	996	4.62
	NN (PHA)	990	4.55
	Double-exponential	991	5.35
	NN (Double-exponential)	987	5.88
Uranium ore 15,445 ppm (609 keV)	PHA	987	4.46
	NN (PHA)	994	4.33
	Double-exponential	991	5.45
	NN (Double-exponential)	990	5.76

V. CONCLUSIONS

This paper presents a neural network-based method for nuclear signal processing, systematically validated using both a single-peak Cs source and uranium ore samples with multiple characteristic peaks. The proposed approach enables the neural network model to directly learn the complex nonlinear relationship between sampled signals and energy labels, thus obviating the need for traditional digital shaping and peak searching steps. Experiments show that the neural network achieves performance on key metrics such as main peak energy resolution and spectral linearity that is highly consistent with the PHA algorithm, regardless of whether the sampling rate is as high as 500 MSPS or as low as 20 MSPS. The model also demonstrates stable reconstruction performance even when the input data are substantially downsampled, indicating strong robustness to input quality. Further experiments confirm that the accuracy of spectral reconstruction is

determined by the quality of the energy labels, as the neural network is able to faithfully reproduce the characteristics of different labels but cannot surpass

their inherent quality. In summary, this neural network-based methodology can greatly simplify the signal analysis workflow, reduce hardware dependencies, and provide novel directions and technical underpinnings for the development of compact, low-cost, and intelligent nuclear detection systems.

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