AI-Driven / Particle Discrimination for the Dual-Scintillator Detector

Authors: Peiyu Zhang, Dr. Lei Wang, Tan, Mr. Yifan, Li, Dr. Haoxuan, Wang, Mr. Zexi, Ms. Yan Li, WANG, Dr. Lei

Date: 2025-08-05T16:48:29+00:00

Abstract

Accurate measurement of the activities of / radionuclides in environmental samples is critical for environmental radiation monitoring. Traditional / discrimination methods for dualscintillator detectors primarily rely on the amplitude, width, and rise time of the pulse from the detector, often leading to crosstalk between / signals and compromising measurement accuracy. To address this limitation, this study designs a composite detector combining dualscintillators with silicon photomultiplier (SiPM) array and proposes a convolutional neural network (CNN) model for / particle signal discrimination. By constructing a lightweight CNN architecture, this method extracts multi-dimensional features from pulse shapes to reach the highprecision classification of / particles. Experimental validation using mixed signals from a 244 Cm -source and a 90 Sr-90 Y -source shows that the CNN method significantly reduces crosstalk ratios: the alpha-to-beta ($\rightarrow$) crosstalk ratio is reduced to 0.25 %, and the beta-toalpha($\rightarrow$) crosstalk ratio to 0 %. Compared with traditional particle discrimination methods such as the Amplitude-and-width Discrimination (AWD) and Integral Rise Time Method (IRTM), these crosstalk ratios are reduced by one order of magnitude, demonstrating the method' s superiority in improving measurement accuracy. This study provides an intelligent, low-cost, and scalable solution for high-precision detection of radioactive contamination in environmental samples, with broad prospects in environmental radiation monitoring.

Full Text

AI-Driven / Particle Discrimination for the Dual-Scintillator Detector

Pei-Yu Zhang[1], Lei Wang[1,*], Yi-Fan Tan[1], Hao-Xuan Li[1], Ze-Xi Wang[1], and Yan Li[1]

[1]Chengdu University of Technology, Chengdu 610059, China

Accurate measurement of / radionuclide activities in environmental samples is critical for environmental radiation monitoring. Traditional / discrimination methods for dual-scintillator detectors primarily rely on pulse amplitude, width, and rise time, often leading to crosstalk between / signals and compromising measurement accuracy. To address this limitation, this study designs a composite detector combining dual-scintillators with a silicon photomultiplier (SiPM) array and proposes a convolutional neural network (CNN) model for / particle signal discrimination. By constructing a lightweight CNN architecture, this method extracts multi-dimensional features from pulse shapes to achieve high-precision classification of / particles. Experimental validation using mixed signals from a ^{2} Cm -source and a Sr- Y -source shows that the CNN method significantly reduces crosstalk ratios: the alpha-to-beta ($\rightarrow$) crosstalk ratio is reduced to 0.25%, and the beta-to-alpha ($\rightarrow$) crosstalk ratio to 0%. Compared with traditional particle discrimination methods such as Amplitude-and-width Discrimination (AWD) and Integral Rise Time Method (IRTM), these crosstalk ratios are reduced by one order of magnitude, demonstrating the method' s superiority in improving measurement accuracy. This study provides an intelligent, low-cost, and scalable solution for high-precision detection of radioactive contamination in environmental samples, with broad prospects in environmental radiation monitoring.

Keywords: / discrimination; convolutional neural network; silicon photomultiplier; crosstalk ratio; dual-scintillator detector

Introduction

With the rapid development of nuclear energy and nuclear technology, environmental monitoring requirements for artificial radionuclides have become increasingly stringent. In radiation protection and environmental monitoring, accurate measurement of extremely low activities of artificial radionuclides (especially total and total activities) in environmental samples is crucial for evaluating radiation risks and ensuring environmental safety [**?**, **?**]. Artificial radionuclides in the environment (such as emitters ^{2} Cm and $^{2\ 1}$Am, emitters Sr- Y, and emitters ^{131}I) can be directly measured through the particles they release [**?**, **?**, **?**].

Detectors used for / nuclide measurement mainly include gas detectors, semiconductor detectors, and scintillation detectors. Compared with gas detectors, scintillation detectors generally exhibit higher detection efficiency and sensitivity, as well as more compact sizes. In contrast to semiconductor detectors, they often offer advantages in cost and radiation damage resistance [**?**, **?**]. However, scintillation detectors commonly suffer from / signal crosstalk when simultaneously detecting and particles, which limits measurement accuracy [**?**].

Dual-scintillator detectors, composed of a ZnS(Ag) scintillator and a plastic scintillator, represent a common solution to this challenge. Their working principle is as follows: particles are primarily absorbed by the ZnS(Ag) layer and converted into optical signals, while higher-energy particles tend to penetrate the ZnS(Ag) layer and are detected by the subsequent plastic scintillator. This design enables simultaneous / particle measurement through physical separation [?].

For the output signals of dual-scintillator detectors, traditional particle discrimination methods mainly rely on Amplitude-and-width Discrimination (AWD) and Integral Rise Time Method (IRTM). AWD utilizes statistical differences in amplitude and width between and particle pulses for differentiation. However, this method faces practical challenges: the selection of optimal discrimination thresholds often depends on experience, and due to the correlation between pulse width and amplitude, complete separation of / particles is difficult. The $\rightarrow$ crosstalk ratio may exceed 5%, significantly affecting measurement accuracy [?, ?, ?, ?]. IRTM employs the rise time differences of optical signals generated by and particles in the scintillator. Nevertheless, the rise time of signals is also influenced by amplitude, leading to a high crosstalk ratio in this method [?, ?].

In summary, the pulse signals generated by and particles in dual-scintillator detectors exhibit significant overlap in amplitude distribution. Although traditional methods utilize energy information and partial temporal characteristics of signals, their ability to precisely distinguish / particles remains limited.

In recent years, Artificial Intelligence (AI) technologies have demonstrated tremendous potential in nuclear signal processing due to their powerful pattern recognition capabilities and have been successfully applied to tasks such as neutron-gamma (n-) discrimination and - particle discrimination. For example, a feedforward neural network method applied to signals from a BC-501 liquid scintillation detector achieved misidentification rates of only 1.34% and 1.28% for neutron and gamma ray discrimination, respectively [?]. Fully Connected Neural Networks (FC-NN) and Recurrent Neural Networks (RNN) applied to stilbene scintillation detectors achieved misidentification rates of 1% and 1.8% for neutron-gamma discrimination [?]. A Multi-Layer Perceptron (MLP) neural network used for online heavy ion identification achieved an accuracy exceeding 99% for ^{12}C and ^{13}C ions [?]. Backpropagation (BP) and Genetic Algorithm-Optimized Backpropagation (GA-BP) methods employed to discriminate / particle waveforms output by a large-area 2 multi-wire proportional counter (gas detector) achieved accuracies of 99% and 95%, respectively [?].

These studies indicate that AI algorithms exhibit excellent performance in complex particle signal discrimination. However, research on intelligent / discrimination for signals from dual-scintillator detectors remains relatively limited, and their potential has not been fully explored in this specific detector configuration.

To address the challenge of / particle discrimination in signals from dual-scintillator detectors, this paper proposes an intelligent discrimination algorithm based on a Convolutional Neural Network (CNN). This method fully uses the fundamental differences in luminescence mechanisms between particles (interacting primarily with ZnS(Ag)) and particles (interacting primarily with the plastic scintillator), which lead to significant distinctions in multiple waveform features such as rise time, pulse amplitude, decay trend, and decay time constants. The CNN model can automatically learn and extract these multi-dimensional features directly from raw pulse shapes, enabling efficient and high-precision / particle classification. Experimental results demonstrate that the CNN method significantly outperforms traditional methods in discrimination performance, showcasing extremely high accuracy and substantial advantages in reducing crosstalk ratios. This provides a high-precision, low-cost, and scalable solution for environmental radiation monitoring, holding broad application prospects. Furthermore, this paper briefly discusses the interpretability of the CNN model in signal discrimination tasks.

2.1. Detector Based on Dual-Scintillator and SiPM Array

This study designed a composite detector based on a dual-scintillator-coupled silicon photomultiplier (SiPM) for high-precision discrimination of / particles in environmental samples, as shown in Fig. 1 [Figure 1: see original paper]. The detector consists of a plastic scintillator coated with a ZnS(Ag) layer and ON Semiconductor FJ60035 SiPMs. To improve photon-collection efficiency, the SiPMs are arranged in an array with an active-area diameter of 52 mm. The ON Semiconductor FJ60035 SiPM has the following key performance indicators: at a working voltage of 27.5 V (Vbr + 2.5 V), the gain reaches approximately 3.4 × 10 , ensuring the distinguishability of single-photon-level signals; the photon-detection efficiency (PDE) is 38%–50% at 450 nm, matching the emission wavelength of the ZnS(Ag)/plastic scintillator; the dark current is controlled within 0.9–7.5 µA, and the dark-count rate is 50 kHz/mm² (21 °C), effectively suppressing background noise and enhancing sensitivity to low-activity samples; the rise time is 90–250 ps, ensuring the temporal resolution of the pulse waveform. These parameters and their contributions jointly ensure the efficient discrimination and precise detection of / particles by the detector [**?**].

The ZnS(Ag) scintillation layer has a thickness of approximately 10 mg/cm² and is directly sprayed onto the surface of the plastic scintillator, forming a coincidence scintillator capable of simultaneous / particle measurement. The ZnS(Ag) crystal, with Ag as the luminescence center, emits 450 nm fluorescence when particles excite electrons to the conduction band; these electrons are then captured by Ag and release energy through radiative transition [**?**, **?**]. The detection efficiency of the ZnS(Ag) scintillation layer for particles is close to 100%. This blue light penetrates the thin plastic scintillator layer and is received by the SiPM. Due to the very thin ZnS(Ag) scintillation layer, its sensitivity to particles is low, thus effectively suppressing -induced crosstalk.

The plastic scintillator (type: BC-404) achieves detection through fluorescence molecular energy transfer. The energy of particles is absorbed by the matrix and transferred to the primary scintillator PPO (2,5-diphenyloxazole), which emits photons upon de-excitation. The wavelength shifter POPOP (1,4-bis(2-(5-phenyloxazolyl)) benzene) absorbs these photons and emits 420 nm fluorescence, which is ultimately converted into an electrical signal by the SiPM [?, ?, ?]. The dual scintillator detector distinguishes / particles based on their different interaction mechanisms, reducing / crosstalk from the source.

2.2. Background Shielding

To obtain clean / particle signal samples and ensure the reliability of the training data, it is necessary to minimize the influence of environmental background and cosmic rays on the dataset. This paper adopts lead shielding and anti-coincidence techniques to reduce the background [?, ?, ?]. In this study, a 10 cm thick lead shielding layer is selected to effectively attenuate the impact of environmental radiation, a choice validated by Monte Carlo simulation methods.

In the experimental design, anti-coincidence measurements are employed to exclude high-energy cosmic rays. The main detector detects particles released from standard and sources, while the anti-coincidence detector identifies background radiation and cosmic rays from the surrounding environment. When rays interact with both the main detector and the anti-coincidence detector and generate signals almost simultaneously, these signals are determined to be background signals and are excluded. Through the dual mechanism of physical shielding and anti-coincidence logic discrimination, the purity of the signal data in the training samples is significantly improved, providing a reliable dataset foundation for subsequent analysis.

2.3. Signal Acquisition and Sample Processing

To enhance the output signal strength, signal-to-noise ratio, and sensitivity of the detector, the main detector employs a SiPM array to convert the light signal from the scintillator. The signal is then processed by a signal summation circuit, an amplification circuit, a pole-zero cancellation circuit, and a single-ended-to-differential conversion circuit before being digitized by a high-speed ADC (Analog-to-Digital Converter) [?, ?]. Given that the output signal from the SiPM array is relatively weak, the amplification circuit amplifies the signal strength. The pole-zero cancellation circuit, as a crucial technique, effectively mitigates the exponential undershoot at the tail of the nuclear pulse signal, which is caused by charge redistribution in the detector and the parasitic capacitance of the circuit, thereby restoring a smooth output waveform. The main detection circuit is depicted in Fig. 2a [Figure 2: see original paper].

When processing high-frequency signals, environmental electromagnetic interference and common-mode noise can easily lead to signal distortion. Differential input offers superior stability and anti-interference capability compared to single-ended input. The high-speed ADC operates at a sampling rate of 80 MSPS and is controlled by an FPGA. Within the FPGA, a FIFO is employed to buffer the digital pulse signals, with each sample comprising 576 data points, each separated by a time interval of 12.5 ns.

The anti-coincidence detector, comprising a plastic scintillator coupled with a SiPM array, is designed to detect -rays and cosmic rays. Its output signal is processed through an amplification circuit, a pole-zero cancellation circuit, and a comparator circuit to generate a rectangular pulse signal used for anti-coincidence veto logic. This signal is then sent to the FPGA for anti-coincidence discrimination. The acquisition board is visualized in Fig. 2b [Figure 2: see original paper].

In the and particle waveform acquisition experiment, the radioactive source was positioned at the center of a sample tray, which was then placed inside the lead-shielded detector housing' s detection chamber, as illustrated in Fig. 2c [Figure 2: see original paper]. The distance between the source and the detector was set to 3 mm. The and sources used in the measurements were a ² Cm source and a Sr- Y source, respectively.

Within the FPGA, the output signals from the anti-coincidence detector were utilized to suppress background events detected by the main detector, thereby retaining only the pulses originating from the / sources. Subsequently, digital baseline restoration was applied to remove the DC offset, optimizing the CNN' s waveform feature extraction capability. The cleaned digital pulse signals produced by / particles were then transmitted to the host computer via an Ethernet interface. Fig. 2d [Figure 2: see original paper] shows the entire signal chain from SiPM to host computer, including key modules like pole-zero cancellation and FIFO buffer.

Data acquisition and preprocessing are critical steps for achieving accurate detection of and particle signals. Detailed information on the and particle signal datasets used in this study is provided in Table 1 . This paper employs mean filtering and normalization for preprocessing digital pulse signals, aiming to optimize the quality of training signals and improve model training performance. The calculation formulas for mean filtering and normalization are given by Eq. (1) and Eq. (2), respectively. Mean filtering smooths the signals by computing the average within a local window, reducing high-frequency noise while preserving the main features of the signals. Amplitude normalization of the signals unifies the feature scales, accelerates model convergence, and enhances training efficiency [**?**, **?**, **?**]. The results of signal data processing are presented in Fig. 3 [Figure 3: see original paper].

$$y_i = \frac{1}{2k+1}\sum_{j=-k}^{k} y_{i+j} \quad (1)$$

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (2)$$

where y_i represents the value of the filtered signal at position i, y_{i+j} is the value of the original signal at position $i + j$, k is the radius of the filtering window with a window size of $2k + 1$, x_{norm} is the normalized value, x is the original data value, x_{min} is the minimum of the original data, and x_{max} is the maximum of the original data.

2.4. Characteristics of Pulse Signals Generated by / Particles

and particles exhibit significant differences in physical properties, leading to distinct waveform features in the detector, as shown in Table 2 . Physically, particles have larger mass, strong ionization ability, but weak penetrability, while particles have smaller mass, relatively weak ionization ability, but strong penetrability. When particles interact with the ZnS(Ag) scintillator, their high energy deposition density excites numerous Ag ions, causing extensive electron transitions and capture, resulting in large signal amplitude. The longer excited-state lifetime of Ag ions gives particles a signal duration with a decay time of 200 ns.

In contrast, particles have stronger penetrability, passing through the ZnS(Ag) layer without significant interaction and reaching the plastic scintillator layer. The low energy deposition density of particles results in fewer excited PPO and POPOP molecules, leading to smaller signal amplitude. The rapid energy transfer and de-excitation process of PPO gives particles a shorter signal duration with a decay time of 2.4 ns. From the perspective of pulse shape features, these physical property differences lead to distinctly different pulse shapes for and particles in the composite scintillator. particles exhibit high luminescence efficiency in the ZnS(Ag) scintillator, with large-amplitude and long-duration fluorescence pulses, while particles show low luminescence efficiency in plastic scintillator, with small-amplitude and short-duration fluorescence pulses. Such waveform features based on differences in energy deposition density and excited-state lifetime provide a physical basis for particle identification and discrimination [**?**, **?**, **?**]. This fundamental distinction enables the CNN model to learn and extract discriminative features from pulse shapes, as elaborated in detail in Sec. 3.

During the transmission of alpha particles, physical processes such as self-absorption, air attenuation, and interaction with the detector lead to energy loss. Consequently, the statistical spectrum of energy deposition of alpha particles in the detector exhibits a low-energy tail. Relying solely on amplitude discrimination may result in misclassification: low-energy alpha particles could be mistaken for beta particles, while some high-energy beta particles might be misidentified as alpha particles, thereby causing channel crosstalk. As shown in Fig. 4 [Figure 4: see original paper], a comparison of the pulse signal shapes of alpha and beta particles indicates that their signals may overlap in both amplitude and width, leading to potential confusion.

3.1. CNN for Alpha-Beta Particle Discrimination

This section systematically presents the design principles, network architecture, and key parameters of the proposed lightweight CNN for / particle pulse waveform classification. The model is implemented with Python 3.10.11 and PyTorch 2.5.1, and all training and validation are conducted on a hardware platform equipped with an Intel i5-12500H processor.

To fully leverage the advantages of CNNs in local feature extraction, this study converts the collected one-dimensional time-series data into two-dimensional matrices. Originally developed for two-dimensional image processing, CNNs excel at capturing local patterns, making them equally applicable to our reshaped waveform data. To prevent the output size from shrinking due to convolution operations, zero-padding is employed to ensure that the output features maintain the same dimensions as the input features. The convolutional layer performs feature extraction by sliding a convolution kernel over the input data, with convolution defined in Eq. (3). The stride is set to 1, which not only preserves the correlation information of adjacent data points and ensures the integrity of local feature extraction but also avoids losing key details by reasonably controlling the interval at which the convolution kernel traverses the data.

$$y_{i,j} = \sum_m \sum_n k_{m,n} \cdot x_{i+m,j+n} + b \quad (3)$$

where $k_{m,n}$ represents convolution kernel weights, $x_{i+m,j+n}$ is the local region of the input feature map, b is the bias term, and $y_{i,j}$ is the corresponding pixel value of the output feature map.

In this study, the proposed model architecture is illustrated in Fig. 5 [Figure 5: see original paper]. Table 3 presents the parameter settings for each layer of the CNN, including specific details such as layer type, filter size, and activation function. The model input is a preprocessed 3D tensor with a shape of 24 × 24 × 1, derived from the original one-dimensional waveform data. The model structure comprises two convolutional layers, each followed by a batch normalization layer and a ReLU activation function. The mathematical expression of ReLU is given in Eq. (4).

$$f(x) = \max(0, x) \quad (4)$$

The pooling layer uses max pooling to reduce the dimensionality of feature maps, lowering computational complexity while retaining key features. The fully connected layer flattens the extracted feature maps, further integrating feature information and enhancing classification accuracy. The output layer is designed based on task requirements, specifically tailored to the needs of particle classification in low-background / measurement scenarios. It is configured with 2 neurons, which assign probabilities via the Softmax function—corresponding to the classification of particles and particles, respectively—allowing the model to clearly distinguish between the two particle types and perform binary classification in practical measurements.

The CNN model effectively extracts features from one-dimensional waveform data and performs classification analysis through a combination of convolutional layers, batch normalization layers, activation functions, pooling layers, and fully connected layers. This model structure is designed to balance feature extraction capability, computational complexity, and generalization performance, thereby making it suitable for waveform data analysis tasks. Through this design, the CNN can fully leverage local features in one-dimensional waveform data to achieve high-precision discrimination between and particles. During model training, batch normalization layers help accelerate convergence and improve model stability, while the non-linear characteristics introduced by the ReLU activation function enable the model to learn more complex feature representations. By integrating the extracted feature information, the fully connected layers further enhance the model' s classification accuracy, ensuring the accurate completion of the classification task.

Results

During model training, the cross-entropy loss function was adopted as the optimization objective, and network parameters were updated using the Adam optimizer. Through iterative optimization on the training set, model parameters were continuously adjusted to minimize the loss function. The validation set was used to monitor the model's generalization performance in real time during training. When the validation loss reached its minimum, the corresponding model parameters were saved, indicating optimal generalization capability under the current configuration. Key hyperparameters (e.g., learning rate, batch size) were fine-tuned through multiple rounds of experiments to ensure consistent performance on both the training and validation sets, thereby guaranteeing expected performance on the test set.

The discrimination results and error rates of the model on the validation set are presented in Table 4 . The validation set contained 400 -particle (^{2} Cm) samples, of which 399 were correctly identified and 1 was misclassified as a -particle (error rate: 0.25%); it also included 400 -particle (Sr- Y) samples, all of which were correctly identified with no misclassifications (error rate: 0%). These results demonstrate that the proposed CNN model exhibits excellent discrimination capabilities for distinguishing between and particle signals, achieving high-precision classification with extremely low error rates. The model achieved near-zero error levels for both particle types.

To verify the effectiveness of the CNN in / pulse waveform discrimination, we compared its discrimination results with traditional methods, such as AWD and IRTM. AWD is widely used in nuclear physics and radiation detection. Since the pulse signal amplitudes and widths generated by and rays in composite scintillators usually differ significantly under normal conditions, this method can be used to discriminate between them. By setting appropriate discrimination thresholds and combining pulse amplitude and width information, the crosstalk rate can be effectively reduced, detection efficiency can be improved, and discrimination of and pulse signals can be achieved. This method uses the change in pulse width to distinguish signals, thereby compensating for the possible shortcomings of relying solely on amplitude discrimination.

IRTM is based on the characteristic that the integral value of the pulse signal changes with time. When a particle passes through the detector, a pulse signal is generated, and the intensity (or amplitude) and shape of this signal depend on the type and energy of the particle. By calculating the integral value of the pulse signal (that is, the total sum of the signal intensity over time), the trend of the integral value increasing with time can be observed. As the number of integration points increases, the growth rate of the integral value gradually slows down and eventually approaches a stable value, which is called the integral constant [?, ?]. Since the pulse trailing edge of particles drops rapidly and their energy deposition process is short, compared with particles, the pulse integral rise time of particles is shorter. This characteristic enables the integral value of particles to reach a stable value within a short period of time, making it convenient for rapid discrimination. In this paper, two threshold parameters for the rise time are selected as 15% and 95%.

In terms of evaluating the performance of the classification model, the confusion matrix serves as a key tool that can visually display the comparison between the predicted results of the model and the actual results in different categories. In this study, we used three different models to analyze the discrimination of pulse signals. Fig. 6 [Figure 6: see original paper] shows the confusion matrices of these three models on the test set and the corresponding distribution of classification results.

Fig. 6a presents the confusion matrix for the amplitude-and-width-based particle-discrimination method. A total of 325 events and 393 events were correctly identified; nevertheless, 75 events were misclassified as events and 7 events as events. Fig. 6b shows the corresponding probability distributions, with red bars denoting events and blue bars events. Although separation is achieved, the misclassification rate indicates limited accuracy. Fig. 6c gives the confusion matrix for IRTM. This approach achieves higher accuracy, correctly predicting 388 events and 400 events. Only 12 events are misclassified as events, and no events are misclassified as events, demonstrating excellent -particle discrimination with minor -particle mislabeling. Fig. 6d displays the probability distribution of the rise-time method. The -particle probability is concentrated between 0 and 0.2, whereas the -particle probability is concentrated between 0.8 and 1.0, indicating effective separation and high discrimination power. Fig. 6e shows the confusion matrix for the CNN-based method. The CNN correctly classifies 398 events and 400 events, misclassifying only one event as and no events as , demonstrating outstanding accuracy. Fig. 6f presents the probability distribution of the

CNN method. The -particle probability is tightly clustered between 0 and 0.2, and the -particle probability between 0.8 and 1.0, indicating nearly perfect separation with negligible overlap.

Meanwhile, the crosstalk ratio is introduced to further evaluate model performance. The calculation formulas for the crosstalk ratio are as follows, and the crosstalk ratio results of different discrimination methods are shown in Table 5 . The calculation formula for the $\rightarrow$ crosstalk ratio is shown in Eq. (5):

$$X_{\alpha\rightarrow\beta} = \frac{N_{\alpha\rightarrow\beta}}{N_{\alpha\rightarrow\beta} + N_{\alpha}} \quad (5)$$

where $N_{\alpha\rightarrow\beta}$ is the number of particles mispredicted as and N_{α} is the number of particles predicted as .

The calculation formula for the $\rightarrow$ crosstalk ratio is shown in Eq. (6):

$$X_{\beta\rightarrow\alpha} = \frac{N_{\beta\rightarrow\alpha}}{N_{\beta\rightarrow\alpha} + N_{\beta}} \quad (6)$$

where $N_{\beta\rightarrow\alpha}$ is the number of particles mispredicted as and N_{β} is the number of particles predicted as .

The results comparison demonstrates that the CNN model achieves the highest accuracy on the test set, highlighting its superior performance in classification tasks. The CNN-based discrimination method not only shows significant advantages in classification accuracy but also possesses powerful feature extraction and generalization capabilities, enabling effective processing of complex signal features. This advantage arises from the CNN model' s ability to automatically learn and optimize feature representations, reducing the need for manual feature selection and thus improving the efficiency and robustness of the classification process.

Analysis

AWD is characterized by a simple algorithm and high computational efficiency, enabling rapid extraction of key static features (amplitude and width). However, its ability to capture time-domain characteristics is limited, and the lack of in-depth analysis of the signal' s dynamic evolution may result in the loss of subtle features. Experimental results (Table 5) show an $\rightarrow$ crosstalk ratio of 18.75% and a $\rightarrow$ crosstalk ratio of 1.75%, indicating limited accuracy for complex signal classification tasks.

IRTM, as a typical time-domain technique, extracts the rise-time feature, effectively capturing dynamic characteristics. Experimental data (Table 5) yield an $\rightarrow$ crosstalk ratio of 3.0% and a $\rightarrow$ crosstalk ratio of 0%, outperforming

AWD. Nevertheless, its performance under highly complex or noisy conditions remains to be improved.

The CNN exhibits superior performance in time-domain signal analysis. Convolutional layers automatically learn local spatiotemporal features, capturing dynamic information. Trained with these features, the network learns intrinsic signal patterns and delivers high-precision classification. Experimental data (Table 5) reveal an $\rightarrow$ crosstalk ratio of only 0.25% and a $\rightarrow$ crosstalk ratio of 0%, significantly surpassing both AWD and IRTM. CNN thus markedly reduces inter-particle misclassification and is particularly suited to complex time-domain signal processing that demands high accuracy.

In summary, AWD suffices for low-precision, simple classification tasks; IRTM is effective for time-domain feature extraction but limited in complex scenarios; while CNN demonstrates outstanding classification performance, substantially enhancing the accuracy and reliability of signal discrimination. Experimental evidence confirms that CNN offers a robust technical solution for high-precision particle identification.

Impact of Data Preprocessing and Model Architecture

Data preprocessing steps play a key role in improving model performance. Baseline correction, mean filtering, and normalization not only enhance the quality of input data but also facilitate model convergence and training efficiency. By removing baseline drift and reducing high-frequency noise, the main features of pulse signals are retained, enabling the CNN to focus on learning the essential features for distinguishing and particles.

The CNN architecture, which combines convolutional layers, batch normalization layers, activation layers, and pooling layers, has proven effective in extracting and classifying features from pulse shape data. The hierarchical feature learning approach allows the model to capture both local and global signal features, providing a comprehensive representation for accurate identification. The use of batch normalization and ReLU activation functions helps address the vanishing gradient problem and accelerate the training process, making the model more applicable to practical applications. Additionally, CNN has significant advantages in processing high-speed pulse signals. Its parallel computing architecture can leverage hardware acceleration using GPUs, and the parallel computing characteristics of convolution kernels enable simultaneous feature extraction at multiple positions, greatly improving computational efficiency. Compared with traditional methods, CNN can capture multiple feature types such as signal amplitude, width, and rise time simultaneously, more comprehensively reflecting signal characteristics, thus achieving efficient processing of high-speed signals.

Discussion on Error Sources

The sources of error in this study mainly include the following aspects. In the data-preprocessing stage, mean filtering and normalization were employed. Although mean filtering smooths the signal and suppresses high-frequency noise, it may also blur salient features such as the pulse rise time and shape. To improve preprocessing performance, more advanced techniques—such as adaptive filtering or wavelet transform—will be considered for more effective signal-noise separation.

The CNN model comprised two convolutional layers with a learning rate of 0.001 and a batch size of 32. These hyperparameters strongly affect model performance; an overly high learning rate can destabilize training, whereas an overly low rate slows convergence. Future work will adopt refined optimization techniques (e.g., Bayesian optimization or genetic algorithms) to automatically tune these parameters and enhance both performance and generalization.

The experimental setup employed a ^{2} Cm source and a Sr- Y source. The dataset contained 6400 -particle and 6400 -particle samples. Although representative, the dataset may not encompass all potential environmental disturbances or signal variations. Fluctuations in equipment performance and ambient conditions can also introduce additional uncertainties. Subsequent experiments will therefore incorporate stricter environmental controls (including temperature stabilization and electromagnetic shielding) and expand the dataset to cover broader environmental conditions, thereby improving model robustness.

Conclusion

This study has successfully developed an AI-driven / particle discrimination system for dual-scintillator detectors, demonstrating significant advancements in environmental radiation monitoring. By integrating convolutional neural networks with the composite ZnS(Ag)/plastic scintillator detection system, we have achieved breakthrough performance in particle discrimination accuracy. Results showed the CNN model outperformed traditional methods significantly in / particle classification. The alpha-to-beta crosstalk ratio was as low as 0.25%, and the beta-to-alpha crosstalk ratio was 0%. Compared to AWD ($\rightarrow$ crosstalk ratio of 18.75%) and IRTM ($\rightarrow$ crosstalk ratio of 3%), the CNN achieved an order-of-magnitude improvement.

The system' s core innovation lies in its end-to-end feature learning mechanism. It automatically extracts waveform differences of / particles in ZnS(Ag)/plastic scintillators, such as rise time and decay constants. Combined with a lightweight network architecture, it overcomes the limitation of traditional methods that rely on manual feature engineering, offering a high-precision and low-cost solution for low-background environmental monitoring. In the future, we will continue to optimize the system' s real-time performance and plan to conduct field validation to further advance the intelligent development of nuclear emergency response technology.

With its powerful feature extraction and generalization capabilities, the CNN can efficiently process complex signal features, automatically learn key patterns, and accurately identify critical information. This reduces dependence on manual feature extraction and enhances system stability and reliability. In conclusion, the CNN shows unique advantages in signal discrimination under complex conditions, indicating great potential in environmental radioactivity monitoring. It is expected to provide more accurate and reliable technical support for monitoring applications and lay a solid foundation for the intelligent development of environmental radioactivity monitoring technology.

References

[1] A. X, G. L. Qian, G. Q. Ge, et al., Determination of gross and activities in Zouma River based on online HPGe gamma measurement system. NUCL SCI TECH. 31(12), 67–78 (2020). doi:10.1007/s41365-020-00828-0

[2] J. He, Y. Shao, M. Luo, et al., Research progress on the distribution of anthropogenic radionuclides in Northwest China. J ENVIRON RADIOACTIV, 285, 107678 (2025). doi:10.1016/j.jenvrad.2025.107678

[3] Y. Morishita, S. Yamamoto, K. Izaki, et al., Optimization of thickness of GAGG scintillator for detecting an alpha particle emitter in a field of high beta and gamma background. RADIAT MEAS, 112, 1–5 (2018). doi:10.1016/j.radmeas.2018.02.003

[4] K. Saito, I. Tanihata, M. Fujiwara, et al., Detailed deposition density maps constructed by large-scale soil sampling for gamma-ray emitting radioactive nuclides from the Fukushima Dai-ichi Nuclear Power Plant accident[J]. J ENVIRON RADIOACTIV, 139(Sp. Iss. SI), 308–319 (2015). doi:10.1016/j.jenvrad.2014.02.014

[5] D. Dietrich, F. Medici, Artificial radionuclides in the sediments of the Rhône river: a snapshot of the situation during winter 1994/95[J]. TERRA NOVA, 8(5), 430–434 (1996). doi:10.1111/j.1365-3121.1996.tb00768.x

[6] W. Chen, R. An, X. Wan. Development status of low-background / measurement techniques. Chinese J. Radiat. Heal. 25(4): 288–292 (2016). doi:10.1016/j.cjrh.2016.04.008 (in Chinese)

[7] Y. Zhao, S. Jin, X. Zhuang, et al. Current status and development of nuclear safeguards detectors. Atom. Energy+ 58(S2): 438–451 (2024). doi:10.7538/yzk.2024.youxian.0396 (in Chinese)

[8] M. Qiao, Y. Ren, J. Wang, et al. Research on anti-coincidence nuclear radiation detector circuits. P. Autom. Instrum. 44(S1): 299–303 (2023). doi:10.1007/s11516-023-00849-3 (in Chinese)

[9] D. Badocco, C. Cester, D. Filippi, et al. Realization and characterization of a protective coating for plastic scintillators used as sensors of radioactive contaminants in water. NUCL INSTRUM METH A, 906(OCT.21):50-55 (2018). doi:10.1016/j.nima.2018.07.083

[10] G. Ranucci, A. Goretti, P. Lombardi. Pulse-shape discrimination in organic liquid scintillators. NUCL INSTRUM METHODS, 412(2-3):374–386 (1998). doi:10.1016/S0168-9002(98)00456-2

[11] P. Chandrikamohan, T. A. Devol. Comparison of Pulse Shape Discrimination Methods for Phoswich and CsI:Tl Detectors. IEEE T NUCL SCI, 54:398-403 (2007). doi:10.1109/TNS.2007.892943

[12] B. S. Budden, L. C. Stonehill, Warniment A, et al. Handheld readout electronics to fully exploit the particle discrimination capabilities of elpasolite scintillators. NUCL INSTRUM METHODS, 795(sep.21):213–218 (2015). doi:10.1016/j.nima.2015.06.004

[13] B. D' Mellow, M. A. Aspinall, R. Mackin, et al. Digital discrimination of neutrons and -rays in liquid scintillators using pulse gradient analysis. NUCL INSTRUM METH A, 578(1):191-197 (2007). doi:10.1016/j.nima.2007.04.174

[14] A. Jones, M. Joyce. Pulse-shape discrimination in organic scintillators using rising edge. doi:10.1109/animma.2013.6727923

[15] F. Seitz, B. Bennett, F. Thomson. Pulse shape discrimination of EJ-276 with SiPM readout. EPJ WEB CONF, 288(000):5 (2023). doi:10.1051/epjconf/202328806010

[16] E. Ronchi, P. Åderström, J. Nyberg, et al. An artificial neural network based neutron–gamma discrimination and pile–up rejection framework for the BC-501 liquid scintillation detector. NUCL INSTRUM METH A, 610(2):534-539 (2009). doi:10.1016/j.nima.2009.08.064

[17] F. Fu, F. A. D., S. D. Clarke, et al. Artificial neural network algorithms for pulse shape discrimination and recovery of piled–up pulses in organic scintillators. ANN NUCL ENERGY, 120(oct.):410–421 (2018). doi:10.1016/j.anucene.2018.05.054

[18] R. Jiménez, M. Sánchez-Raya, J.A. Gómez-Galán, et al. Implementation of a neural network for digital pulse shape analysis on a FPGA for on-line identification of heavy ions. NUCL INSTRUM METH A, 2012. doi:10.1016/j.nima.2012.01.034

[19] G. L. Qian, B. J. Zhu, Y. Lv, et al. Artificial neural network algorithm for pulse shape discrimination in 2 and 2 particle surface emission rate measurements. NUCL SCI TECH, 34(10):91-102 (2023). doi:10.1007/s41365-023-01305-0

[20] ON Semiconductor. J-Series SiPM Sensors [EB/OL]. Semiconductor Components Industries, LLC, 2018. [2025-07-21]. https://www.onsemi.com

[21] A. S. Y., B. I. A., B. T. H. Optical fiber-based ZnS(Ag) detector for selectively detecting alpha particles. APPL RADIAT ISOTOPES, 169 (2020). doi:10.1016/j.apradiso.2020.109495

[22] H. Kim, K. Park, B. Han, et al. Study on ZnS(Ag) for alpha spectrometer using silicon based photo sensor. J INSTRUM, 15(10): P10020 (2020). doi:10.1088/1748-0221/15/10/P10020

[23] A. F. Adadurov, P. N. Zhmurin, V. N. Lebedev, et al. Plastic scintillators with -diketone Eu complexes for high ionizing radiation detection. APPL RADIAT ISOTOPES, 69(10):1475-1478 (2011). doi:10.1016/j.apradiso.2011.05.022

[24] V. G. Vasilchenko, V. G. Lapshin, A. I. Peresypkin, et al. New results on radiation damage studies of plastic scintillators. NUCL INSTRUM METHODS, 369(1):55–61 (1996). doi:10.1016/0168-9002(95)00774-1

[25] P. Buzhan, B. Dolgoshein, E. Garutti, et al. Timing by silicon photomultiplier: A possible application for TOF measurements. NUCL INSTRUM METH A, 2006. doi:10.1016/j.nima.2006.05.142

[26] C. Ouyang, Z. Pan. BH1216 type dual-channel low background mea-

surement instrument. NUCL. ELECTRON. DETECT. TECHNOL. 23(4): 6 (2003). doi:10.3969/j.issn.0258-0934.2003.04.014 (in Chinese)
[27] J. Feng, Y. Chen, H. Yang. The Background Issue in the Measurement of Low–level Gamma-ray. NUCL. ELECTRON. DETECT. TECHNOL. 29(3): 167-172 (2009). doi:10.3969/j.issn.0258-0934.2009.03.038 (in Chinese)
[28] L. J. Diao, T. D. Hou, W. Li, et al. Reduction of background in – spectrometer using anti-coincidence and thermal neutron shielding [J]. NUCL TECHNOL. 33(7): 5 (2010). doi:CNKI:SUN:HJSU.0.2010-07-006 (in Chinese)
[29] T. Pu, Y. Qian, H. Su, et al. Design of multi-channel filter shaping chip for PPAC detector. NUCL. ELECTRON. DETECT. TECHNOL. (2015). doi:CNKI:SUN:HERE.0.2015-11-022 (in Chinese)
[30] S. Liu, Y. Gu, X. Cao. Theoretical analysis and experimental verification of pole–zero cancellation circuit. NUCL. ELECTRON. DETECT. TECHNOL. 34(12): 4 (2014). doi:10.3969/j.issn.0258-0934.2014.12.009 (in Chinese)
[31] S. Usuda, S. Sakurai, K. Yasuda, et al. Phoswich detectors for simultaneous counting of –, ( )–rays and neutrons [J]. NUCL INSTRUM METH A, 1997, 388(1):193–198. doi:10.1016/S0168-9002(97)00327-6
[32] Y. Chen, Z. Wang. Quantitative analysis modeling of infrared spectroscopy based on ensemble convolutional neural networks. CHEMOMETR INTELL LAB, 181:S0169743918301904 (2018). doi:10.1016/j.chemolab.2018.08.001
[33] A. Karmakar, A. Pal, G. Kumar, et al. Neutron-gamma pulse shape discrimination for organic scintillation detector using 2D CNN based image classification. APPL RADIAT ISOTOPES, 2025, 217(000). doi:10.1016/j.apradiso.2024.111653
[34] D. N. McKinsey, C. R. Brome, R. Huffman, et al. Time dependence of liquid-helium fluorescence–art. no. 062716. PHYS REV A. Atomic, molecular, and optical physics, 2003, 67(6). doi:10.1103/PhysRevA.67.062716
[35] S. T. Yamamoto. Comparison of light outputs, decay times, and imaging performance of a ZnS(Ag) scintillator for alpha particles, beta particles, and gamma photons. APPL RADIAT ISOTOPES, 2021, 168(1). doi:10.1016/j.apradiso.2020.109527
[36] B. de Celis, et al. Coincidence measurements in / / spectrometry with phoswich detectors using digital pulse shape discrimination analysis. NUCL INSTRUM METHODS, 2007. doi:10.1016/j.nima.2007.05.085

Note: Figure translations are in progress. See original paper for figures.