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Enhanced Neutron-Gamma Discrimination Using Deep Neural Networks for Precision Nuclear Medicine

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Abstract: Scintillator detectors, widely used in nuclear medicine and industrial applications such as radiation monitoring and material analysis, are sensitive to both neutrons and gamma rays (n/γ). A key challenge in neutron detection is minimizing gamma-ray interference to ensure accurate measurements. Neutron-gamma discrimination is difficult because the two particle types often produce overlapping signals in scintillator detectors, with similar pulse amplitudes but subtle differences in shape and timing. Traditional methods struggle to distinguish these subtle features, leading to misclassification and reduced detection accuracy.To address this, we propose a deep neural network (DNN)-based approach combined with pulse shape discrimination (PSD) techniques to achieve high-precision particle discrimination in mixed n/γ fields. Leveraging DNN's ability to learn complex patterns, our method effectively classifies neutron and gamma-ray pulses. The trained DNN model was evaluated against traditional discrimination algorithms, including the charge comparison method, rise-time analysis, frequency-domain gradient analysis, and K-means clustering. Quantitative results demonstrate a discrimination accuracy of 99%, significantly outperforming conventional techniques. Furthermore, the proposed DNN method not only enhances discrimination reliability in mixed radiation fields but also reduces processing time compared to existing methods, making it suitable for real-time applications in medical imaging and industrial neutron detection.

Keywords: neutrons and gamma rays, deep neural network, pulse shape discrimination

Izboljšana razločevanje med nevtroni in gama žarki z uporabo globokih nevronskih mrež za natančno nuklearno medicine

Izvleček: Scinilatorji, ki se pogosto uporabljajo v nuklearni medicini in industrijskih aplikacijah, kot so nadzor sevanja in analiza materialov, so občutljivi tako na nevtrone kot na gama žarke (n/γ). Ključni izziv pri zaznavanju nevtronov je zmanjšanje motenj gama žarkov, da se zagotovijo natančne meritve. Razlikovanje med nevtroni in gama žarki je težko, ker ti dve vrsti delcev v scinilatorjih pogosto proizvajajo prekrivajoče se signale s podobnimi amplitudami impulzov, vendar z neznatnimi razlikami v obliki in časovnem poteku. Tradicionalne metode težko razlikujejo te subtilne značilnosti, kar vodi do napačne klasifikacije in zmanjšane natančnosti detekcije. Da bi to rešili, predlagamo pristop, ki temelji na globoki nevronski mreži (DNN) v kombinaciji s tehnikami razlikovanja oblike impulza (PSD), da bi dosegli visoko natančno razlikovanje delcev v mešanih n/γ poljih. Naša metoda izkorišča sposobnost DNN za učenje kompleksnih vzorcev in učinkovito razvršča nevtronske in gama impulze. Usposobljeni model DNN je bil ocenjen v primerjavi s tradicionalnimi algoritmi razlikovanja, vključno z metodo primerjave naboja, analizo časa vzpona, analizo gradienta v frekvenčnem prostoru in združevanjem K-povprečij. Kvantitativni rezultati kažejo 99-odstotno natančnost razlikovanja, kar znatno presega

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zmogljivosti konvencionalnih tehnik. Poleg tega predlagana metoda DNN ne le izboljša zanesljivost razlikovanja v mešanih sevalnih poljih, ampak tudi skrajša čas obdelave v primerjavi z obstoječimi metodami, zaradi česar je primerna za uporabo v realnem času v medicinskih slikah in industrijskem zaznavanju nevtronov.

Ključne besede: neutroni in gama žarki, globoka nevronska mreža, razlikovanje oblike impulza

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1 Introduction

Neutron detection technology plays a crucial role in various applications within nuclear medicine, including material analysis for medical isotopes [1], ensuring safety in radiopharmaceutical handling [2-3], monitoring environmental radioactivity that could impact healthcare facilities [4], and supporting advanced diagnostic imaging in aerospace medicine [5]. Additionally, it is vital for the nuclear industry to ensure safe and effective medical radioisotope production [6-11]. However, the challenge arises from the omnipresence of γ-rays in the vicinity of neutron sources. Scintillator detectors, which are widely relied upon for neutron detection, are also sensitive to γ-rays [12]. This sensitivity can compromise the accuracy of neutron detection, underscoring the need to enhance detector performance through the development of effective discrimination techniques.

In 1958, Owen [13] first discovered the property of different decay times of blinking light produced by n/γ interacting with scintillator materials, then proposed a pulse shape discrimination (PSD) technique and successfully discriminated n/γ mixed signals using the PSD technique based on analogue circuits. As a result, a large number of researchers have combined digital techniques with earlier discrimination methods that required the construction of analogue circuits, while other digital-based n/γ discrimination algorithms have also been proposed. For example, Jastaniah et al. [14] implemented a rise time algorithm in 2004 based on digital techniques. In 2007, Flaska [15] achieved a charge comparison algorithm and Liu [16] et al. proposed a time-domain pulse gradient algorithm [17], which can reduce the effect of time-domain noise on the discrimination results of n/γ pulse signals. In 2018, Huang [18] applied the K-means clustering algorithm to discriminate n/γ mixed pulse signals to reduce the influence of human factors in the processing. However, these methods face inherent limitations, rise-time analysis struggles with pulse pileup and electronic noise, charge comparison fails when n/γ pulses exhibit similar charge distributions, and K-means clustering requires pre-labeled data and performs poorly with overlapping pulse features. Moreover, the above discrimination methods can only extract signal features from the time domain or frequency domain, relying on a particular signal feature to identify and classify the discriminated information, which requires a long calculation time for the n/γ discrimination results.

Artificial intelligence (AI) techniques have developed rapidly in recent years, and there has been a growing trend to use deep learning (DL) methods to analyse data. Deep learning generally refers to neural networks consisting of interconnected artificial neurons, which combine low-level features to create abstract high-level attributes. It can be used to identify distributed features in data, which plays a key role in modeling artificial intelligence. The advent of this technology offers a new perspective and an innovative approach to the rapid prediction of complex tasks. DL is not only applicable to computer science fields such as natural language processing [19] and computer vision [20] but also be applied to interdisciplinary studies such as the mechanical design of materials [21], biosensors [22], marine research [23], redox flow batteries [24], and nanogenerator performance prediction [25]. The combination of AI algorithms and PSD techniques has evolved significantly, transitioning from early feature-augmented approaches to hybrid systems that merge PSD features with neural networks, and finally to modern end-to-end deep learning models capable of raw pulse classification without manual feature extraction. The combination of AI algorithms and PSD techniques has also achieved good results in the field of n/γ signal discrimination. In 1998, the first application of AI algorithms to n/γ signal discrimination was proposed by Cao [26] et al., who used the time-of-flight method to identify particle species and verify the feasibility of the algorithm. Esposito [27] and Ronchi [28] used AI algorithms to solve the signal stacking problem well during 2004-2009, respectively. And then, Liu [29] and Zhou [30] further developed neural network algorithms in the field of n/γ pulse signal discrimination. Despite these advances, earlier AI methods still faced challenges such as limited accuracy and high computational costs, necessitating further innovation in model architecture and training efficiency.

This paper uses deep neural network (DNN) algorithms to address the problems of n/γ signal discrimination. DNNs were specifically chosen for this task due to their exceptional capability in handling complex pattern recognition problems, which can discover subtle, non-linear relationships in the temporal and spectral characteristics of n/γ signals that are often imperceptible to conventional analysis techniques. The test samples are compared with the charge comparison algorithm, rise time algorithm, frequency domain gradient analysis algorithm, and K-means clustering algorithm, and the DNN discrimination method can successfully discriminate n/γ mixed pulse signals. The results show that the proposed DNN discrimination method not only provides effective discrimination of the mixed radiation fields but also improves the discrimination time compared with other discrimination methods. This dual advantage of high accuracy and computational efficiency makes the DNN approach particularly suitable for real-time applications in nuclear medicine and industrial radiation monitoring, where both precision and speed are critical requirements.

2 Materials and methods

2.1 Scintillator detector principle

Neutrons cannot directly cause ionization or excitation of matter, so they cannot be detected directly [31]. However, scintillator detectors are sensitive not only to neutrons but also to γ-rays, which can be helpful for the detection of n/γ mixed pulse signals [32]. When neutrons or γ-rays are irradiated in the scintillator detector, the atoms in the astragalus crystal can be ionized and excited. Weak scintillation photons are generated when the atoms jump from the excited state back to the ground state. The photomultiplier tube converts these weak scintillations into photoelectrons after the photoelectrons enter the photomultiplier tube through the electro-optical input system. The photoelectrons are multiplied and all electrons are collected by the anode of the photomultiplier tube to form a pulse signal digital (PSD) and then enter the signal processing circuit [33]. The commonly used scintillator neutron detector consists of four parts, including scintillator material,

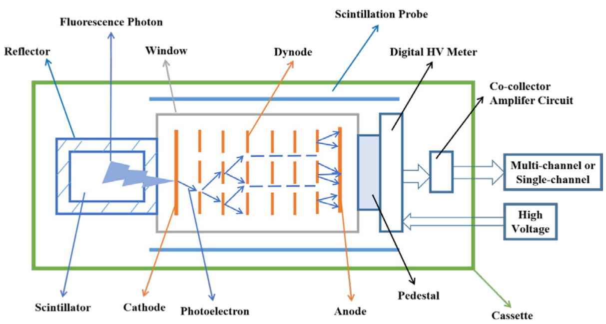

Figure 1: Working principal diagram of scintillator detector.

photomultiplier tube, high voltage supply unit, and electronics. The structure of the scintillator neutron detector is shown in Fig. 1.

2.1 Data processing

We have considered the experiments in reference [34] with a neutron source of ^{252}Cf and a detector module using the plastic scintillator EJ-299-33. The power supply unit provides the operating voltage for the photomultiplier, which amplifies the scintillation light produced by the scintillator under the irradiation of the neutron source ^{252}Cf and transforms it into a pulse signal. The amplified signal is then transferred to a 12-bit 65 MS/PS digital converter, where the ADC converts the amplified analog signal into a digital signal. The digital signal is transmitted via an optical bridge to a computer for subsequent processing and analysis.

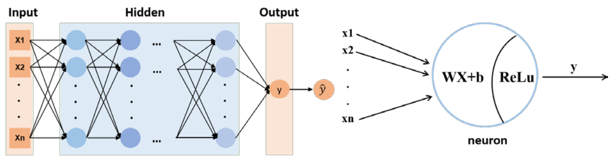

Figure 2: The workflow of the DNN modeling process.

As shown in Fig. 2, the DNN model with input, hidden, and output layers are proposed to implement neutron and γ-rays discrimination. The layers of the model are connected in a fully connected manner, with any neuron in layer ***i*** necessarily connected to any neuron in layer ***i+1*** [35]. Each local model is composed of a linear relationship and an activation function. The input x is used to provide the initial information (including PSD corresponding to neutrons and gamma rays), which is then propagated to the hidden units in each layer to produce the output categories y. The data information flows forward through the network to achieve forward propagation until a scalar cost function Cost is generated, and the back propagation is achieved when the information of the cost function flows backward through the network to calculate the gradient. All data samples are used for training and evaluation of the model, and the cross-entropy loss error $J(\boldsymbol{\theta})$ is used to evaluate the accuracy of the model with the formula.

$$\mathrm{Cost} = \min_{\theta} J(\theta) \tag{1}$$

$$J(\theta) = -\frac{1}{N}\sum_{n=1}^{N} y_n \log \hat{y}_n + (1-y_n)\log(1-\hat{y}_n) \tag{2}$$

Where θ is the optimal parameters, N is the number of samples, y_n $\mathbf{y_n}$ is the DNN model output value, and $\hat{y}_n$ is the test value.

The cost function can be decomposed into the sum of the cost functions of each sample, and a small batch of samples is drawn uniformly from the training set using the stochastic gradient descent algorithm (SGD). When the training set size M grows and m remains constant, the estimate of the gradient g can be expressed as:

$$g = \frac{1}{\mathrm{M}} \nabla_\theta \sum_{i=1}^{m} \mathrm{Cost}(x^{(i)}, y^{(i)}, \theta) \tag{3}$$

$$\theta \leftarrow \theta - \alpha g \tag{4}$$

where $x^{(i)}$ is the $\boldsymbol{i}$-th sample, $y^{(i)}$ is the true label of the $\boldsymbol{i}$-th sample, and α is the learning rate.

The SGD enables the training of deep network models on large-scale data. For a fixed-size model, the computation of each step of stochastic gradient descent update does not depend on the size of the training set, thus effectively reducing the computational cost of the model with good fitting performance. The relevant parameter settings are as follows, the corresponding network outputs of neutron and γ-ray events are 1 and 0, the epochs are 3000, the batch size is 256, the optimizer is SGD, the learning rate is 0.000001, the momentum is 0.9, and the early stop is 200. The model environment is a Windows 10 system, 2.3 GHz Intel Core (TM) i7–11800 H GPU, 16.0 GB memory, 3050Ti graphics card, utilizing Python 3.8, Pytorch 1.9.0 + cuda 11.1.

3 Results

3.1 Discrimination results based on DNN

In this research, the data of neutron pulse signal and γ-rays pulse signal from 252Cf scintillation detectors are extracted using Python tools, and the sampled 7291 pulse signals are used to construct the data set, which is divided into an 80% training set and a 20% test set. The deep neural network algorithm model is constructed to achieve the classification process of neutron and γ-rays particle identification, as shown in Fig. 3 and Fig. 4. The training samples of 5832 pulse signals are fed into the DNN model, and the discrimination results of the training set are shown in Fig. 3. The neutron and gamma samples in the training set are well discriminated out. Fig. 4 shows the discrimination results of 1459 test samples of n/γ mixed pulse signals into the trained DNN network. Since the pulse signals in both the training and test sets are well discriminated out, the DNN model can separate the mixed n/γ well.

3.2 Comparative analysis of results

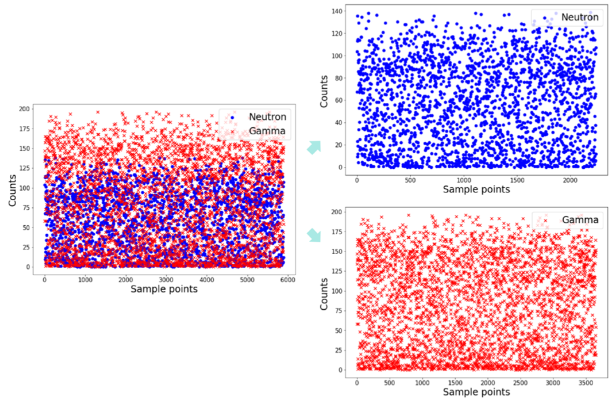

Figure 3: The discrimination results of DNN on the training set. Blue means neutrons and red means gamma rays.

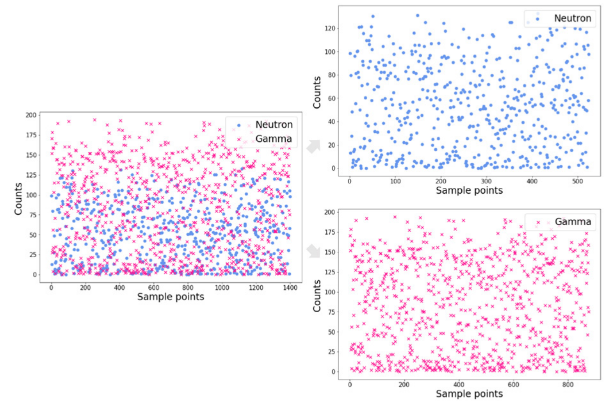

Figure 4: The discrimination results of DNN on the test set. Blue means neutron and red means gamma rays.

The discrimination results using the charge comparison algorithm (Fig. 5a), the rise time algorithm (Fig. 5b), the frequency domain gradient analysis algorithm (Fig. 5c), and the K-means clustering algorithm (Fig. 5d) are shown in Fig. 5, respectively. The five discrimination methods are used to discriminate the same 5000 sets of n/γ mixed pulse signals and the results showed that they are all successful in discriminating the n/γ mixed pulse signals, as shown in Table 1. In terms of discrimination accuracy, the discrimination accuracy rate (DAR) is improved compared to other discrimination algorithms, the DNN achieves the highest accuracy (DAR_N: 99.60%, DAR_G: 99.93%), outperforming charge comparison (99.20%, 99.86%) due to its ability to automatically learn subtle pulse-shape features. Rise-time analysis shows significantly lower neutron accuracy (89.75%, 98.19%) because of overlapping rise times in mixed radiation fields, while K-means clustering performs worst (75.77%, 95.72%) as its unsupervised approach struggles with overlapping pulse distributions. In terms of speed, the DNN is fastest (1.6s), being twice as quick as traditional methods (3-4s) and four times faster than K-means (6.4s), thanks to GPU processing. Traditional methods like charge comparison and frequency-domain gradient analysis are slower due to per-pulse mathematical operations, while K-means suffers from iterative distance calculations. The DNN clearly provides the best balance, offering superior accuracy with significantly reduced processing time, making it ideal for real-time applications. Charge comparison remains a viable alternative where marginal accuracy loss is acceptable or DNN deployment is constrained, whereas K-means should only be considered when labeled training data is unavailable. The results demonstrate that while all methods can discriminate n/γ pulses, the DNN delivers optimal performance where both precision and speed are critical.

$$DAR_{\_N} = (1 - \frac{|N_{Pre\_N} - N_{Mea\_N}|}{N_{Mea\_N}}) \times 100\% \quad (5)$$

$$DAR_{\_G} = (1 - \frac{|N_{Pre\_G} - N_{Mea\_G}|}{N_{Mea\_G}}) \times 100\% \quad (6)$$

Where N_{Pre_N} represents the number of correctly discriminated neutron pulse signals, N_{Mea_N} represents the number of neutron pulse signals tested, N_{Pre_G} represents the number of correctly discriminated gamma pulse signals, and N_{Mea_G} represents the number of gamma pulse signals tested.

In implementing the five discrimination algorithms, it is found that each discrimination method has its advantages. The charge comparison algorithm is the simplest in principle, therefore, the easiest of all the discrimination methods to implement. Although the largest difference between the neutron and γ-ray pulse signals is only in the falling edge of the pulse, the rising time algorithm maximizes the difference between the two particle-induced signals by taking into ac-

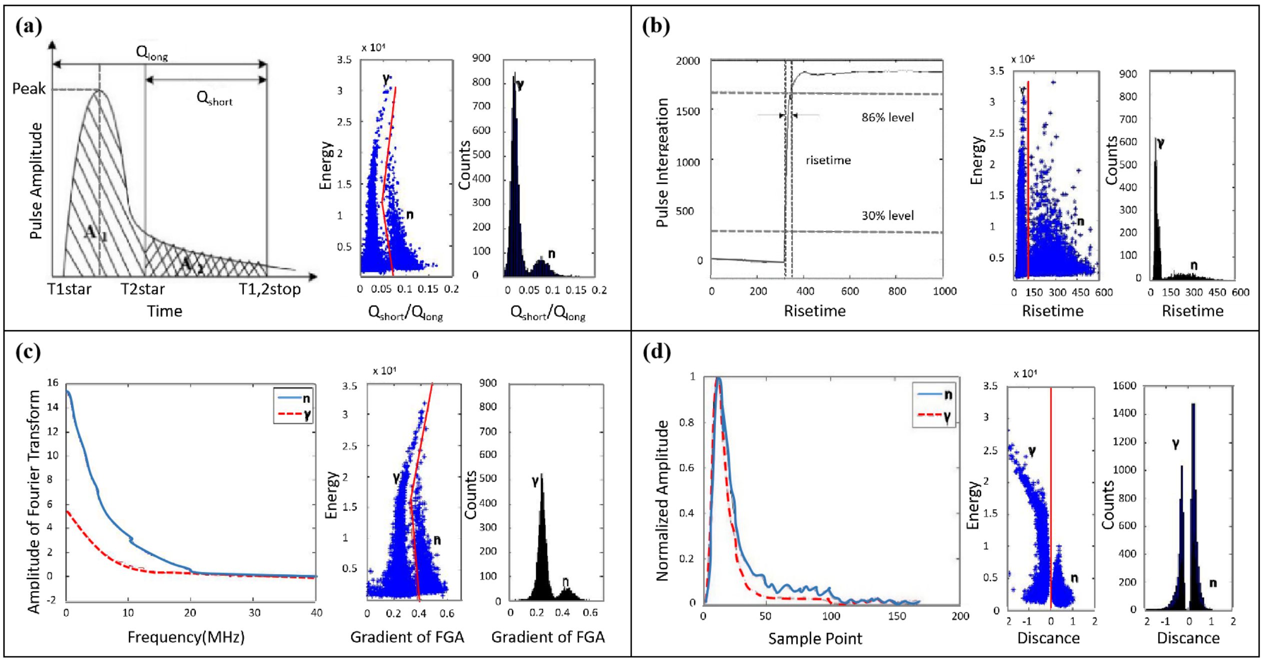

Figure 5: Four discrimination algorithms. (a) Charge comparison integration time scale diagram and charge comparison algorithm discrimination results. (b) Signal of time integration and rise time algorithm discrimination results. (c) The spectrum graph of the n/γ signal and the discrimination result of the frequency domain gradient analysis algorithm. (d) Two cluster centers are determined by K-means and the after-time integration result of the K-means clustering algorithm.

Table 1: Comparison of the results of five n/γ discrimination methods

Method	Neutron	Gamma	DAR_N	DAR_G	Time
Charge Comparison	757	4243	99.20%	99.86%	3.4s
Rise time	828	4172	89.75%	98.19%	3.5s
Frequency Gradient Analysis	742	4258	98.80%	99.79%	3.9s
K-means Clustering	933	4067	75.77%	95.72%	6.4s
DNN	748	4252	99.60%	99.93%	1.6s

count the rising and falling edges of the entire pulse signal in extracting the eigenvalues. The frequency domain gradient analysis algorithm is more resistant to interference by extracting features in the frequency domain, so it is not sensitive to changes in the shape of the pulse caused by noise. The K-means clustering algorithm does not rely on the selection of time windows to extract features in the separation of n/γ mixed pulse signals and can make direct judgments on signal categories without the need for prior parameter adjustment. However, the existing discrimination methods need to be further improved in terms of discrimination time and accuracy. The number of n/γ obtained using the five discrimination methods in this paper is relatively consistent, indicating that the discrimination process based on the DNN algorithm in this paper can successfully discriminate n/γ mixed pulse signals. This method enables the accuracy of n/γ mixed pulse signal discrimination to be improved and the computation time to be reduced.

4 Conclusions

This paper investigates the discrimination of neutrons and γ rays from scintillator detectors by combining PSD and DNN algorithms. The particle pulse signal data samples are collected from the scintillator detector and divided into training and test samples. We use the training samples to train the DNN model and realize the discrimination of the particles in the test samples. We compare the result with other discrimination methods, such as the charge comparison algorithm, the rise time algorithm, the frequency domain gradient analysis algorithm, and the K-means clustering algorithm. The five discrimination methods are applied to the same 5000 sets of n/γ mixed pulse signals. The results show that all five methods can successfully discriminate the n/γ mixed pulse signals, and the number of n/γ obtained is more consistent. In addition, the DNN method has improved the discrimination time compared with other methods, indicating that the DNN model proposed in this paper is feasible for n/γ discrimination.

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6 Conflict of interest statement

The authors declare that there are no conflict of interests.

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