

# Recognition of $\alpha$ and $\beta$ Radiation Waveforms Based on Neural Networks

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**Abstract:** Alpha and beta radiation do not possess penetrating properties to the skin, but they can adhere to the surface of the human skin. Inhalation through the mouth and nose often poses a greater risk to the human body compared to gamma radiation. Traditional methods for identifying alpha and beta particles have some drawbacks, such as high requirements for equipment's signal-to-noise ratio and significant impact of noise on identification results. We propose the utilization of lightweight neural network models for alpha and beta particle identification. These models exhibit strong generalization and robustness, enhancing the ability to resist noise interference during the identification process. Additionally, their lightweight nature facilitates deployment on devices, thereby contributing to the prevention of nuclear proliferation to some extent.

**Keywords:**  $\alpha\beta$  Ray recognition, lightweight neural networks, nuclear diffusion.

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## 1. Introduction

With the increasing global risk of nuclear leaks, humanity is facing ever greater risks from nuclear sources. Nuclear radiation refers to particles or electromagnetic radiation emitted by radioactive nuclides, primarily  $\alpha$ ,  $\beta$ , and  $\gamma$  rays. Among them,  $\gamma$  rays have the strongest penetrating power, and their hazards are well recognized. They can penetrate the skin, causing DNA strand breaks. This DNA damage can trigger DNA repair processes, but if not properly or completely repaired, it may lead to genetic mutations and the development of cancer[7].

Studies have shown that  $\alpha$  and  $\beta$  radiation have a more severe impact on human life. The penetrating power of  $\alpha$  and  $\beta$  rays is not as strong as that of  $\gamma$  rays;  $\alpha$  rays can be blocked by materials as thin as a sheet of paper, and  $\beta$  rays cannot penetrate human skin. However, if nuclear wastewater is discharged into the ocean and evaporates to form rainwater,  $\alpha$  and  $\beta$  particles may float in the air, forming aerosols that adhere to the human body. If not properly addressed,  $\alpha$  and  $\beta$  particles can enter the body through the mouth and nose, causing severe damage to human organs, tissue damage, tumor development, and possibly genetic mutations, increasing health risks for future generations.

Waveform recognition technology has been widely applied in various fields such as nuclear waste management, radiation detection and analysis, and nuclear reactor monitoring. Traditional waveform recognition techniques rely on comparing waveform peaks with predefined thresholds for identification. Due to its simplicity and ease of deployment, traditional waveform recognition plays an irreplaceable role in many domains. However, it still has certain limitations.

This paper proposes the use of artificial neural networks for waveform recognition, employing artificial intelligence algorithms to contrast with traditional methods. We focus on the recognition of  $\alpha$  and  $\beta$  radiation in nuclear radiation to enhance identification accuracy.

## 2. Contribution of This Study

The dataset of  $\alpha$  and  $\beta$  waveforms used in this paper is generated from desensitized radiation sources emitting  $\alpha$  and  $\beta$  rays, resulting in waveform data of electrical signals. Currently, it is difficult to find datasets specifically related to  $\alpha$  and  $\beta$  in existing open-source repositories. The dataset we utilize will be made open-source for future researchers to study.

2. This study is the first to employ artificial intelligence methods for the recognition of  $\alpha$  and  $\beta$  waveforms. This innovative approach aims to address the limitations of traditional methods by reducing the possibility of confusion, thereby minimizing measurement errors. We will further elaborate on this in subsequent articles.

## 3. Traditional Methods for the Identification of $\alpha$ and $\beta$ Particles

Traditional waveform identification methods, such as threshold detection and peak analysis, are still widely employed in industry and research due to their simplicity and ease of implementation. This section introduces these traditional methods and assesses their limitations in modern applications.

X-rays emitted by a radioactive source pass through a scintillation crystal, undergo absorption and convert to luminescence, then enter a photomultiplier tube. Within the photomultiplier tube, secondary electron emission occurs in stages, followed by entering signal processing circuits, resulting in pulse-form output signals. Ultimately, these signals are collected and converted into discrete signals through an Analog-to-Digital Converter (ADC). Typically, the recognition of  $\alpha$  and  $\beta$  particles is based on their different bandwidths and the varying number of points within their peak intervals. However, these methods have drawbacks, as there is a potential for confusion. In scenarios where  $\beta$  radioactivity is high, both pulse width and amplitude increase, leading to the misidentification of  $\alpha$  as  $\beta$ . Conversely, if  $\alpha$

radioactivity is high, both pulse width and amplitude decrease, causing misidentification of  $\beta$  as  $\alpha$ . With increasing measurement requirements, there are demands for the  $\alpha$  channel ratio and  $\beta$  channel ratio of the equipment, especially when the radioactive source activity is high, resulting in a sharp increase in the  $\beta$  channel ratio, making it challenging to meet measurement requirements. Neural network models, with their strong generalization and robustness, can partially overcome these limitations and facilitate rapid identification.

In traditional waveform analysis, threshold detection is a common signal processing technique. It identifies critical waveform features by setting a fixed signal threshold. For instance, to identify  $\alpha$  waveforms, a threshold is set so that only signals with peaks exceeding this threshold are considered valid waveforms. The main advantages of this method lie in its simplicity and low computational resource requirements, making it suitable for environments with limited hardware constraints. Traditional methods, due to their straightforward algorithms, ease of implementation, and deployment, are particularly effective in resource-constrained settings. Moreover, these methods usually do not require complex training processes and can quickly adapt to new application scenarios. In fields such as seismic signal monitoring or straightforward mechanical fault diagnosis, traditional methods have been successfully applied for many years, offering stable and reliable performance[5-6].

However, these methods perform poorly when dealing with complex or noise-intensive signals. They often struggle to adapt to subtle waveform variations and have limited accuracy when classifying diverse waveforms. Additionally, threshold setting usually requires manual adjustment based on experience, limiting its adaptability and flexibility.

In contrast, artificial intelligence methods, especially those based on deep learning models, provide higher accuracy and the ability to recognize complex patterns. Although these models incur higher computational costs, their adaptability and learning capabilities from data make them excel in handling variable and nonlinear waveforms, outperforming traditional methods in scenarios with high waveform diversity and potential confusion.

## 4. Based on Artificial Neural Networks for The Identification of $\alpha$ and $\beta$

### 4.1. Dataset

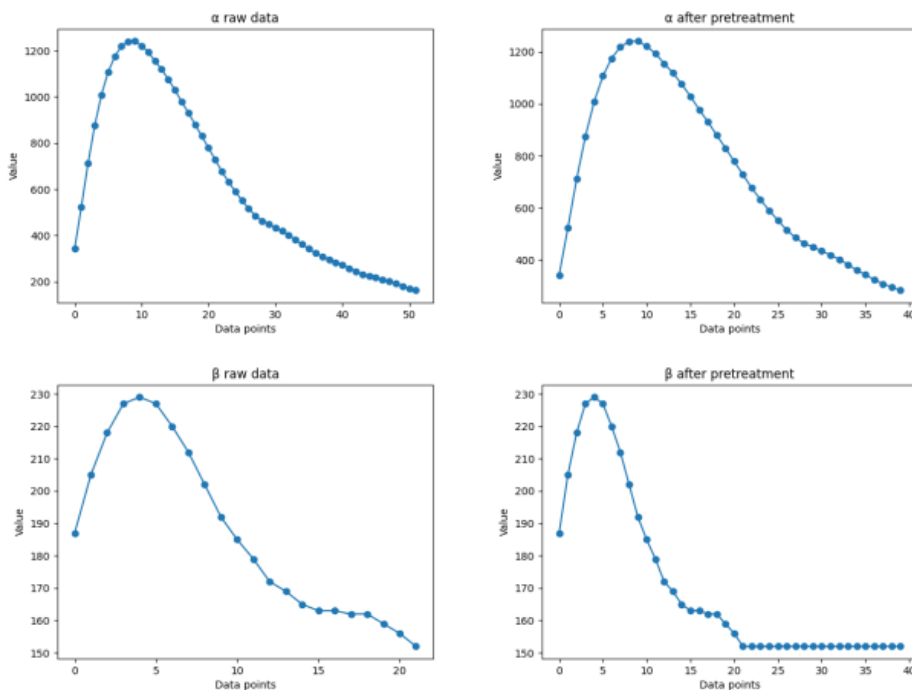
In the context of waveform recognition using artificial neural networks, preprocessing of  $\alpha$  and  $\beta$  data is necessary to ensure that they are input as data of equal length. The data used for training the model are obtained from collected  $\alpha$  and  $\beta$  data from radioactive nuclide sources, extracted using an oscilloscope. The following indicates the quantity of data:

**Table 1.** Information of Datasets

Datasets	$\alpha$ training_set	$\beta$ training_set	$\alpha$ testing_set	$\beta$ testing_set	training_set	testing_set
Quantity	796	1720	250	250	2516	500

Since our model requires fixed-length sequential data, and the features of the data mainly reside in the characteristic peaks of the sequence, but due to the varying bandwidths of these peaks, the length of  $\alpha$  characteristic peaks falls within

the range of 50-55, while the length of  $\beta$  characteristic peaks falls within the range of 30-35. Therefore, we employ a fixed length of 40 data points. For  $\alpha$  data, we trim the tail, while for  $\beta$  data, we stretch the tail, as illustrated in the following figure:



**Figure 1.** Datasets Sample

## 4.2. CNN Model

Based on our dataset, we constructed a Convolutional Neural Network (CNN) model. This model employs a series of convolutional layers to learn hierarchical features from the data. Each convolutional layer utilizes a set of filters to extract essential features from the input data. Subsequently, non-linearity is introduced through activation functions, and downsampling is achieved via pooling layers to reduce feature dimensions, thereby enhancing the model's abstraction capabilities and computational efficiency.

Following these convolutional layers, a sequence of fully connected layers is employed to map the learned features to the output space, preparing for the final classification task. During the training process, the network is trained until the specified training steps are reached. A significant number of training iterations are employed to minimize cross-entropy error, ensuring that the model's output closely approximates the target output values. This extended training duration is undertaken at the expense of a higher number of training cycles to enhance the accuracy of the neural network in identifying nuclear species[1-3].

After testing the trained artificial neural network on the testing dataset, the results are as follows:

**Table 1.** Accuracy of CNN Model

Sample Category	$\alpha$	$\beta$
Testing Accuracy	99.8%	99.9%

Based on the data, it can be observed that artificial neural networks exhibit a favorable recognition effect on sample data, and both the features of the dataset and the length of the data contribute to the network's fitting. The parameter count of the trained neural network is 74594, with input data processed in batches of 10, yielding results in the nanosecond range.

Among the 50 collected data points, random noise ranging from 1 to 5 units was introduced. Despite this, the network's recognition accuracy remained above 99%. This demonstrates the network's robustness in recognizing  $\alpha$  and  $\beta$ , even in the presence of random noise.

## 4.3. DSCNN Model

To reduce the parameter count and make the model more lightweight, we replaced the basic convolution with Depthwise Separable Convolution, aiming to decrease the model's parameters and computational complexity while maintaining network performance as much as possible. This type of convolution is particularly useful in environments with mobile devices and limited resources as it significantly reduces the required computational resources and model size[4].

Depthwise Separable Convolution, typically used for two-dimensional data, can also be applied to one-dimensional sequence data. For one-dimensional sequences, the process of depthwise separable convolution is slightly different, but the basic principle remains consistent. In a depthwise convolutional layer, deep convolution is performed on the input sequence. This step involves applying one-dimensional convolutional kernels independently to each channel (or feature). Assuming the shape of the input data is  $[N, C, L]$ ,

where  $N$  is the batch size,  $C$  is the number of channels, and  $L$  is the sequence length[8].

In depthwise convolution, each input channel is processed separately by a single convolutional kernel. Let's assume we have an input sequence  $I$  with dimensions of  $L \times D$ , where  $L$  is the sequence length and  $D$  is the number of channels. The formula is as follows:

$$O_d(l) = \sum_i I_d(l + i) * K_d(i) \quad (1)$$

After the depthwise convolution, a  $1 \times 1$  pointwise convolution (with a kernel size of 1 in the one-dimensional case) is utilized to combine features from different channels. Now, we have an intermediate sequence  $O$  with dimensions of  $L \times D$ . The formula is as follows:

$$P(l) = \sum_d O_d(l) * K(d) \quad (2)$$

Where  $P(l)$  is an element in the final output sequence at position  $(l)$ ,  $(K)$  is the convolution kernel with a size of 1, and it operates across all input channels  $(d)$ . In this step, pointwise convolution integrates features from different channels by applying a convolution kernel of size  $1 \times 1 \times C$ , which can alter the number of channels[9].

In the DSCNN model, the parameter count of the trained neural network is 58,342. The testing accuracy on the same test set is as follows:

**Table 2.** Accuracy of DSCNN Model

Sample Category	$\alpha$	$\beta$
Testing Accuracy	99.7%	99.9%

It can be observed that, compared to the original CNN network, although there is a slight decrease in model accuracy, the parameter count has been reduced by approximately 21.8%. Therefore, replacing convolutions in the CNN model with depthwise separable convolutions has significantly reduced resource usage.

By decomposing the convolution operation into depthwise and pointwise convolutions, it effectively reduces the number of parameters and computational burden while maintaining the ability to process one-dimensional data. This parameter reduction method not only decreases the model size but also helps prevent overfitting and accelerates training speed. This is particularly beneficial for running models on resource-constrained devices such as mobile devices and embedded systems.

## 5. Summary

Although traditional methods still hold an irreplaceable position in certain applications, artificial intelligence methods offer significant advantages when dealing with higher dimensions and complexities. With the improvement of computing capabilities and continuous algorithm optimizations, artificial intelligence is playing an increasingly important role in the field of waveform recognition.

In the context of waveform recognition for alpha and beta particles, it also contributes to restraining nuclear

proliferation, enhancing nuclear security, and providing a certain degree of contribution. As computational power and algorithmic capabilities continue to advance, the role of artificial intelligence in waveform recognition, particularly for  $\alpha$  and  $\beta$  particles, is expected to grow, furthering its impact on nuclear safety and security.

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