Preliminary Results of Cosmic-Ray Recognition for a Plastic Scintillation Detector Using Machine Learning

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***Abstract*— This study explores the application of machine learning, specifically a one-dimensional Convolutional Neural Network (1D-CNN), to discriminate signals from cosmic rays and background radiation using only a single plastic scintillation detector. A comprehensive dataset, combining signals from cosmic ray and gamma events, was collected for this machine learning approach. The 1D-CNN model, constructed using the Keras library with TensorFlow as the backend, was optimized using the Stochastic Gradient Descent (SGD) optimizer and sparse categorical cross-entropy as the loss function. The proposed model achieved promising results, demonstrating its ability to reliably distinguish between signals from cosmic-ray and gamma events.**

***Index Terms*— Plastic scintillator, cosmic rays, Pulse Shape Discrimination, machine learning (ML), 1D-CNN.**

I. Introduction

Cosmic rays at ground level result from interactions between primary cosmic rays from outer space and atmospheric molecules, primarily oxygen and nitrogen. The dominant cosmic rays at ground level are highly energetic muons, with smaller amounts of protons, neutrons, electrons, positrons, neutrinos, etc. Together, these constitute approximately 8% of the total natural background radiation sources [1]. Traditionally, to measure the cosmic ray component within the radiation background, coincidence techniques have been employed, utilizing a combination of several detectors to discriminate the events of interest from the background [2][3][4]. In our previous work [5][6][7], we investigated the cosmic-ray angular distribution and muon lifetime using coincidence techniques with plastic scintillation detectors and waveform processing.

In recent years, machine learning techniques have found numerous applications in radiation studies [8][9], demonstrating its efficiency in various fields of radiation research. In this study, we propose the use of a one-dimensional Convolutional Neural Network (1D-CNN) to identify cosmic rays amidst background measurements using a single plastic scintillation detector.

II. Experimental Set Up

A. Plastic scintillation detector

The plastic scintillation detector, shown in Fig. 1, consisted of plastic scintillator plates each 80 cm long, 40 cm wide, and 3 cm thick, mounted to a 40 cm long light guide and optically connected to a Hamamatsu R329-02 photomultiplier tube (PMT) [8], operated by a negative high-voltage supply.

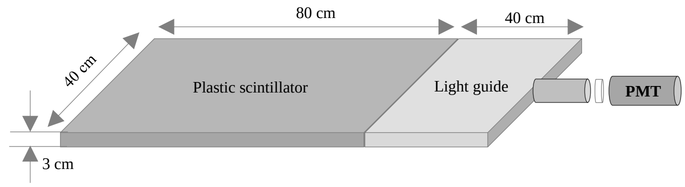


Fig. 1. Plastic scintillation detector.

B. Experimental Setup for ^{60}Co and Cosmic-Ray Measurements

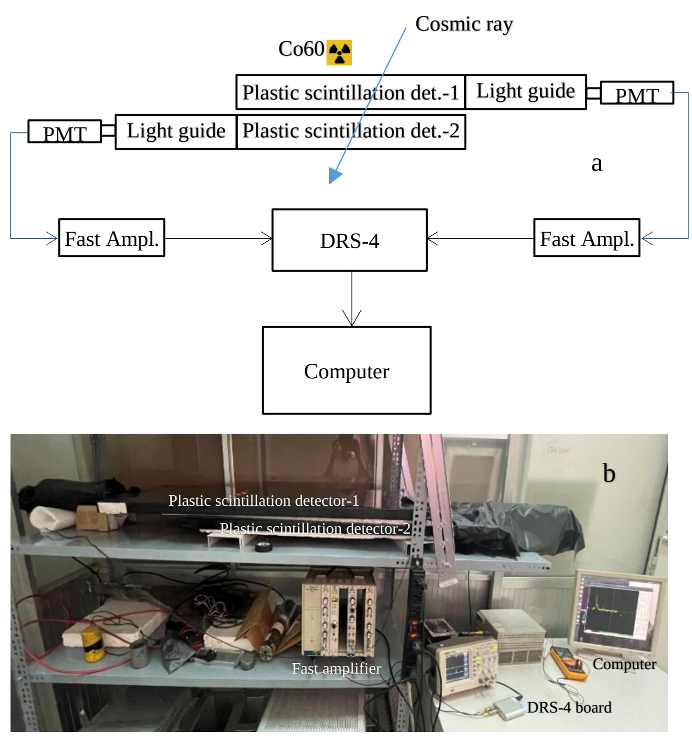
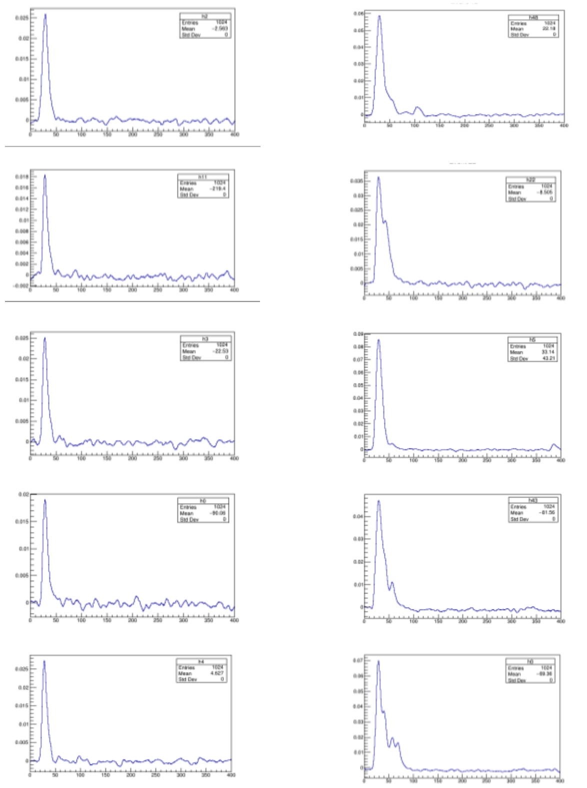


Fig. 2. Experimental setup.
(a). Schematic diagram of gamma and cosmic ray measurements. Waveforms are recorded by the DRS-4 digitizer.
(b) A picture of the experimental setup.

A schematic overview of the experimental setup for gamma and cosmic ray measurements is illustrated in Fig. 2a. For gamma measurements, a ^{60}Co radioisotope source is positioned above the plastic scintillation detector-1. The electronic signal from detector-1 is amplified by a fast amplifier and recorded by the DRS-4 digitizer [9] in the form of waveforms. For cosmic ray measurements, an additional plastic scintillation detector-2 is positioned below detector-1, in parallel. Using coincidence techniques with both detectors, waveforms recorded by the DRS-4 digitizer capture the cosmic ray component. Fig. 2b is a picture of the real experimental setup.

C. Signal Response and Energy Spectrum

Waveform for ^{60}Co gamma events	Waveforms for comic ray events



Note, *horizontal scale is in nsec, and vertical scale is in Volt.*

Fig. 3. Waveforms recorded by the DRS-4 in the plastic scintillation detector-1.
Left: Waveforms for gamma events (^{60}Co).
Right: Waveforms for cosmic rays (coincidence technique).

The signal response for gamma and cosmic rays in plastic scintillation detector-1 is depicted in Fig. 3. The left panel of Fig. 3 shows waveforms recorded from gamma events using a ^{60}Co source, while the right panel illustrates waveforms recorded from cosmic-ray events detected using the coincidence technique. These waveforms exhibit distinct characteristics that are crucial for the machine learning model to discriminate between the two types of events.

To characterize the deposited energy spectrum, digital charge integration (DCI) was applied with a time window of 200 nanoseconds. This technique integrates the charge collected over the specified time window, providing a quantitative measure of the energy deposited by each event. Fig. 4 displays the DCI spectra for gamma and cosmic rays in detector-1. The black curve represents the energy spectrum for gamma events from the ^{60}Co source, while the blue curve represents the cosmic-ray spectrum.

A notable feature in the cosmic-ray spectrum within plastic scintillator material is the well-recognized muon peak. With a 3 cm thick plastic scintillator, the muon peak is estimated to be at 6 MeV (the energy loss rate for a minimum ionizing particle in plastic material is estimated to be about 2 MeV/cm [11]). This peak corresponds to the energy deposition by muon, which is a primary component of cosmic rays at ground level. The presence of this peak is critical as it validates the effectiveness of our setup in accurately detecting high-energy muons using a single plastic scintillation detector.

The ability to distinguish between gamma and cosmic-ray events is further underscored by the distinct energy distributions observed in the DCI spectra. Gamma events, which typically involve lower energy depositions, produce a broad spectrum at lower energies. In contrast, cosmic-ray events, dominated by high-energy muons, exhibit a sharper peak at higher energies.

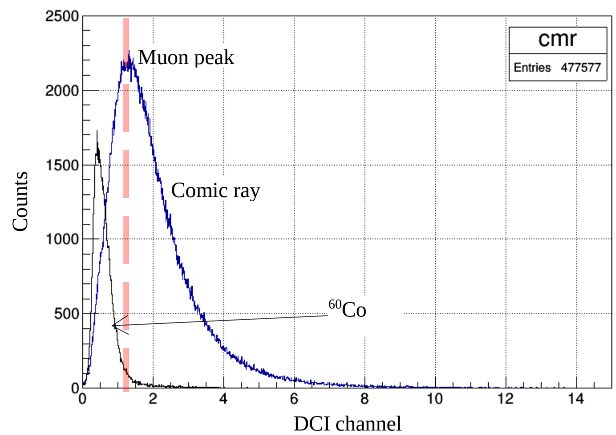


Fig. 4. DCI spectra of ^{60}Co (black) and cosmic rays (blue) for plastic scintillation detector-1. The cosmic-ray spectrum shows a muon peak at approximately 6 MeV.

III. THE MACHINE LEARNING APPROACH

In this work, for the machine learning method, a one-dimensional Convolutional Neural Network (1D-CNN) model is employed. Each waveform sample serves as a unique input, and the model utilizes Rectified Linear Unit (ReLU) activation functions in hidden layers. The Softmax activation function in the output layer provides the classification accuracy for each event.

Dataset Collection:

Our training dataset comprises data from cosmic rays (obtained via coincidence measurement) and gamma rays (from the ^{60}Co source) for detector-1. This dataset includes 78,000 cosmic-ray events and 78,000 gamma events. Cosmic-ray and gamma events are distinctly identified using coincidence measurements and ^{60}Co, respectively, as shown in Fig. 4.

Network Construction:

The construction of our neural network was facilitated by the Keras library with TensorFlow as the backend [5][6]. This specific combination allowed for a robust design process, ensuring an efficient implementation of the 1D-CNN model.

Model Compilation:

Our model was compiled with the Stochastic Gradient Descent (SGD) optimizer, sparse categorical cross-entropy as the loss function, and accuracy as the metric. This configuration was crucial in optimizing the model's ability to distinguish between gamma background and cosmic ray events. The training phase incorporated learning rate decay determined by the following equation: learning rate = $0.1 \times 2^{(-\mathrm{epoch}/60)}$.

Training Configuration:

The training phase utilized 80% of the dataset for training and 20% for validation. After 1,000 epochs, our model demonstrated the ability to distinguish between these events, achieving a validation loss of 0.33 and a validation accuracy of 0.87.

Configuration Overview:

Fig. 5 gives a visual representation of our ML configuration technique. This illustrates the key components and specific design of our 1D-CNN model.

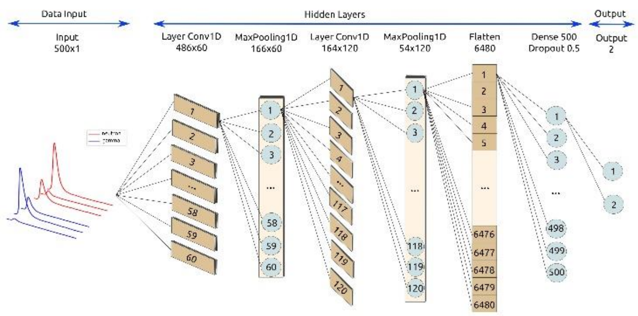


Fig. 5. Machine learning configuration technique. This figure illustrates the key components and design of the 1D-CNN model used in the study.

IV. Results and Discussions

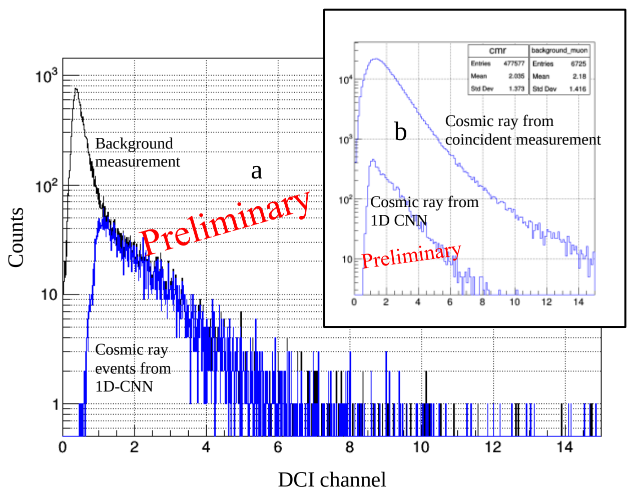


Fig. 6. Radiation background measured in detector-1 (black). Cosmic ray recognition (blue) in detector-1 using the 1D-CNN model.

A detailed analysis of the radiation background measurements for plastic scintillation detector-1 is presented in Fig. 6. The 1D-CNN analysis demonstrated its ability to accurately identify cosmic-ray muons (represented in blue), showing a strong correlation with cosmic-ray measurements obtained using the coincidence technique involving two detectors. This section will describe the performance metrics and comparative analysis with traditional methods.

The initial radiation background measurement, depicted in black in Fig. 6a, provides a baseline for distinguishing cosmic-ray events. By applying the 1D-CNN model, we could extract the cosmic-ray component from this background with a notable accuracy of 1.4% in total. This indicates that our model can reliably identify and isolate cosmic-ray events even within complex and noisy background data.

The precision of the 1D-CNN model is further demonstrated by its ability to recognize the characteristic muon peak, as observed in the energy spectrum of cosmic rays, shown in Fig. 6b. This peak is significant as it validates the model's effectiveness in identifying high-energy muons, which are the primary constituents of cosmic rays at ground level. The presence of this peak confirms the model's accuracy in radiation signal classification.

Furthermore, the validation metrics achieved during the training phase, including a validation loss of 0.33 and a validation accuracy of 0.87 after 1,000 epochs, highlight the efficiency of our model. These results suggest that the 1D-CNN can generalize well to new, unseen data, maintaining high accuracy in differentiating between gamma and cosmic-ray events.

In comparison to traditional coincidence techniques that require multiple detectors to identify cosmic-ray events, our approach simplifies the experimental setup by using a single plastic scintillation detector. This not only reduces the complexity and cost of the setup but also enhances the portability and ease of deployment in various research and field applications.

The integration of machine learning, particularly the 1D-CNN, into cosmic-ray detection represents a significant advancement in the field. Traditional methods, while effective, often involve intricate hardware configurations and manual data analysis. The automation and precision offered by machine learning algorithms streamline the detection process, allowing for real-time analysis and higher throughput of data processing.

V. Conclusions

This study describes a one-dimensional Convolutional Neural Network for differentiating cosmic rays from background measurements within a single plastic scintillation detector. Results from the 1D-CNN analysis illustrated the successful recognition of cosmic-ray muons in the plastic scintillation detector, aligning with measurements obtained through the coincidence technique using two detectors. Our study emphasizes the potential of machine learning techniques in enhancing the precision and reliability of radiation measurements.

Acknowledgment

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