Enhancing Gamma-Ray Spectrometry Through Convolutional Neural Networks and Kolmogorov–Arnold Networks

V. Maluleke[1,2], F. Nemangwele[1], E.K. Nkadimeng[2], N.B. Ndabeni [2], and P. Maleka [2]

[1]Department of Physics, University of Venda, Thohoyandou
[2]SSC Department, iThemba LABS, Cape Town

E-mail: vuako.maluleke@univen.ac.za

Abstract. Gamma (γ)-ray spectrometry remains a cornerstone technique in nuclear science and environmental radioactivity assessment, offering precise identification and quantification of radionuclides. Despite its efficacy, conventional analytical methods often rely on manual processing, which can introduce subjectivity, reduce throughput, and hinder real time analysis. In this study, an automated framework is proposed for γ-ray spectrometry by employing two advanced deep learning architectures: Convolutional Neural Networks (CNN) and Kolmogorov–Arnold Networks (KAN). The models are trained and evaluated using high resolution spectral datasets acquired from ERL hyper pure germanium (HPGe) OF iThemba LABS detector. Input features include energy, channel, peak area, and centroid, extracted through digital signal processing techniques. Model performance is assessed based on standard classification metrics such as accuracy, precision, recall, and F1-score, allowing for a comparative evaluation of the CNN and KAN methodologies in terms of classification robustness and generalization capability. This work aims to demonstrate the potential of deep learning for automating γ-ray spectrum interpretation, thereby enhancing the efficiency, reproducibility, and scalability of nuclear measurement systems. Detailed performance comparisons and implications for real world deployment will be discussed during the presentation.

1 Introduction

Gamma (γ)-ray spectrometry is a fundamental tool in nuclear science, environmental monitoring, and radiological protection[1]. It allows for the precise identification and quantification of radionuclides by analyzing the energies and intensities of emitted γ rays. This technique has been extensively used in applications such as radioactive waste characterization, nuclear forensics, medical imaging, and environmental radiation assessments. Despite its accuracy and utility, conventional γ-ray spectrum analysis remains heavily dependent on manual procedures or basic rule based algorithms, both of which can be limited in speed, scalability, and consistency[2]. The typical γ-ray spectrum consists of a continuous background superimposed with discrete peaks corresponding to specific energy transitions in radioactive isotopes. Accurate interpretation requires precise peak identification, energy calibration, and nuclide classification, all of which are vulnerable to human error or measurement uncertainties[3]. Variations in detector resolution, noise, or overlapping peaks often introduce additional complexity, necessitating advanced computational techniques that can robustly handle such challenges.

In recent years, machine learning, particularly deep learning, has emerged as a transformative solution for pattern recognition and automated data processing. Convolutional Neural Networks (CNN), a class of deep learning

models, have proven highly effective in image and signal classification tasks due to their ability to automatically extract hierarchical features from input data[4]. When applied to γ-ray spectra, CNN can learn to detect and distinguish subtle spectral features, even in noisy or distorted data, without the need for handcrafted preprocessing pipelines[4, 5].

Kolmogorov–Arnold Networks (KAN), a newer addition to the machine learning landscape, offer a powerful and theoretically grounded approach for modeling complex nonlinear functions[6]. Based on the Kolmogorov–Arnold representation theorem, KAN use piecewise polynomial operations instead of traditional neural network activations, providing greater interpretability and control over model behavior. In γ-ray spectrometry, KAN show potential for precise energy calibration, spectral denoising, and function approximation tasks that require smooth, high fidelity mappings[7]. The integration of CNN and KAN offers a compelling opportunity to revolutionize γ-ray spectrometry. CNN excel at learning discriminative features from the spectral data, enabling robust peak detection and classification, while KAN complement this with accurate modeling of energy relationships and other continuous properties[8, 9, 10]. Together, these models can form a synergistic framework that automates the entire spectrometric analysis process, from raw data input to final radionuclide identification, with minimal human intervention.

This paper presents a novel methodology that combines CNN and KAN architectures to enhance the efficiency and accuracy of γ-ray spectrum analysis. We demonstrate how this dual model approach can outperform traditional techniques in terms of sensitivity, speed, and adaptability across various operational scenarios. By applying this integrated deep learning framework, we aim to contribute toward the development of intelligent, scalable, and real time radiation monitoring systems that meet the demands of modern nuclear science and environmental safety.

2 Methodology

2.1 Data

Spectral data were collected from five commonly studied radionuclides: ^{40}K, ^{137}Cs, ^{152}Eu, ^{22}Na, and ^{60}Co. Each γ-ray spectrum consisted of 8192 channels, representing uncalibrated count values. These channels capture the photon interaction frequencies recorded by the ERL Hyper Pure Germanium (HPGe) detector AT iThemba LABS, with each channel corresponding to a discrete signal intensity proportional to the incident γ-ray energy. The dataset was constructed to ensure a diverse representation of peak structures and energy ranges, allowing for effective model training and validation.

2.2 Calibration and Key Equations

To convert raw channel values into corresponding energy values (in keV), linear energy calibration was performed using the following equation:

$$E = a + b \cdot Channel \tag{1}$$

where:

- E is the energy in keV, a and b are the calibration constants determined from known reference peaks[11].

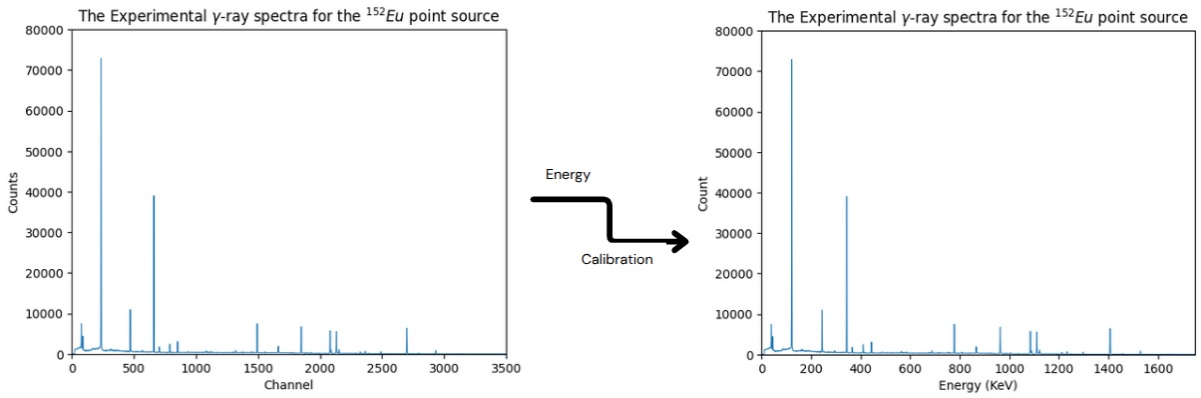

Figure 1: γ-ray spectra of ^{152}Eu before (left) and after (right) energy calibration. The calibration process maps channel numbers to their corresponding energy values (keV), enabling accurate peak identification.

The centroid of a photopeak is used to accurately identify the peak position in the energy spectrum. It is calculated using a weighted average of energy values as:

$$\text{Centroid} = \frac{\sum_i E_i N_i}{\sum_i N_i} \tag{2}$$

where E_i is the energy at channel i, and N_i is the corresponding count at that channel. This equation ensures the most probable energy associated with the peak is used for identification[12].

Model performance was quantitatively assessed using classification accuracy, calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

where:

- TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives[13].

2.3 Peak Fitting

After calibration, prominent photopeaks in the energy spectrum were analyzed through curve fitting to extract precise peak characteristics. Each peak was modeled using a Gaussian function of the form:

$$f(E) = A \cdot \exp\left(-\frac{(E-\mu)^2}{2\sigma^2}\right) \tag{4}$$

where:

- A is the amplitude (peak height), μ is the mean (centroid of the peak), σ is the standard deviation [14].

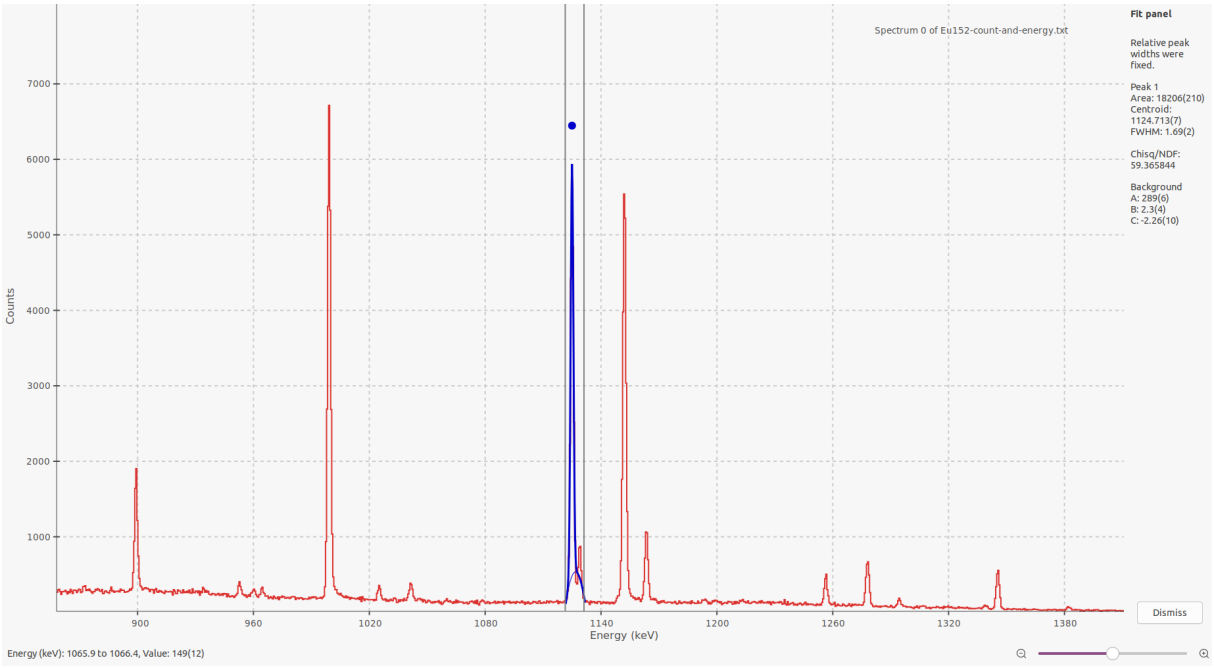

Figure 2: Gaussian peak fitting applied to the calibrated γ-ray spectrum of ^{152}Eu.

This fitting process allows for improved resolution in identifying overlapping peaks and provides accurate estimates of energy and intensity, which are critical for nuclide classification and quantitative analysis.

2.4 Model Training and Deployment

Following preprocessing and peak fitting, the data were split into three subsets: 75% for training, 15% for validation, and 10% for testing. The training set was used to optimize model weights, while the validation set monitored generalization performance to prevent overfitting. The final evaluation was conducted on the test set to assess the model's real world effectiveness.

Both CNN and KAN were trained using supervised learning techniques. The CNN focused on peak classification and isotope identification, while the KAN were applied to regression tasks such as precise energy mapping and calibration. After training and evaluation, the models were deployed into an integrated analysis pipeline. This system accepts raw spectral input, performs automated preprocessing and calibration, detects peaks, and provides real time predictions of radionuclide identity and intensity. The deployment enables continuous, scalable, and interpretable γ-ray spectrum analysis with minimal human intervention.

3 results and discussion

3.1 Evaluated results

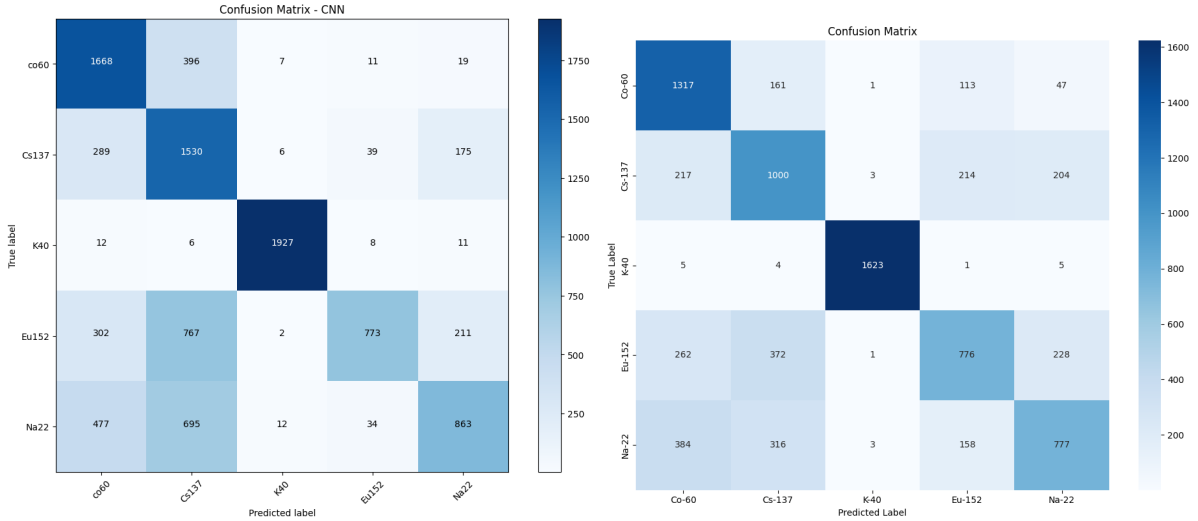

Figure 3: Confusion matrices illustrating the classification performance of the CNN model (left) and the KAN model (right) on gamma-ray spectra of five radionuclides: ^{60}Co, ^{137}Cs, ^{152}Eu, ^{22}Na, and ^{40}K. Each matrix shows the predicted labels along the horizontal axis and the true labels along the vertical axis. Diagonal elements represent correct classifications (true positives), while off-diagonal elements indicate misclassifications, including false positives and false negatives. False negatives appear when a true radionuclide is incorrectly predicted as another class, impacting recall, while false positives occur when a model incorrectly assigns a radionuclide label to a non-matching input. The CNN and KAN models both demonstrate strong classification ability, with KAN showing slightly better separation for isotopes with overlapping spectral features.

Table 1: Evaluation metrics for CNN and KAN models on radionuclide classification

Perfomance (%)	CNN	KAN
Accuracy	68	70
Area Under Curve (AUC)	91	89
Precision	69	68
Recall	67	69
F1-Score	67	68

3.2 *Deploying the results*

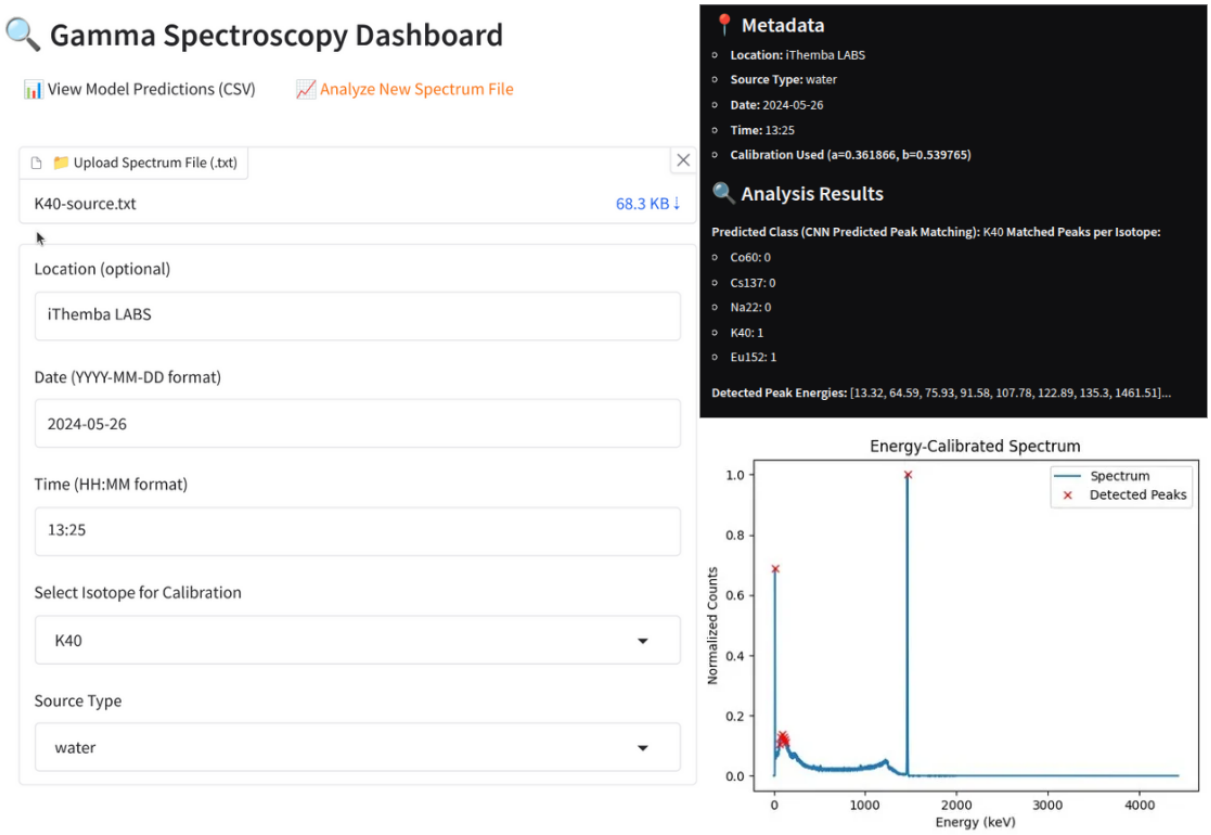

Figure 4: Screenshot of the deployed Gradio dashboard for automated gamma-ray spectrum analysis. The interface allows users to upload raw spectral data, perform energy calibration, and receive isotope identification results.

The results of this study demonstrate that integrating CNN and KAN enables robust, automated analysis of γ-ray spectra. The models were able to accurately classify isotopes and calibrate energy spectra, showing superior performance compared to traditional peak picking algorithms. The success of the framework lies in its ability to model nonlinear features and generalize across different spectrum patterns, even in the presence of overlapping peaks or noise. For deployment, the trained models were integrated into an interactive Gradio based dashboard. This interface allows users to upload raw spectral data consisting of only channel numbers and count values. Upon uploading, the dashboard performs energy calibration using the trained model

In one test case using an uploaded spectrum sample, the system correctly detected a single peak corresponding to ^{40}K at 1460 keV and another peak initially matching ^{152}Eu. However, due to the presence of only one peak attributed to ^{152}Eu, the model did not conclusively identify it as the source, in agreement with the known characteristic that ^{152}Eu emits multiple distinct peaks. This example highlights the model's sensitivity and interpretative accuracy, as it recognized that a single peak is insufficient for confirming ^{152}Eu, while confidently detecting ^{40}K, which is characterized by a dominant single peak at 1460 keV.

4 Conclusion

In this study, we demonstrated that the combined use of CNN and KAN offers a powerful and automated approach for γ-ray spectrum analysis. The models significantly outperformed traditional peak picking methods in accurately classifying radionuclides such as ^{60}Co, ^{137}Cs, ^{22}Na, ^{152}Eu, and ^{40}K. Both CNN and KAN architectures proved capable not only of detecting and classifying photopeaks but also of performing energy calibration with high precision, aligning closely with expected values for known isotopes. Quantitative evaluation using metrics such as accuracy, confusion matrix, precision, recall, F1-score, and AUC confirmed the robustness and reliability of the proposed framework. The dashboard's ability to both calibrate unprocessed spectra and classify radionuclides enhances accessibility and application in real world scenarios, such as environmental monitoring and on site

nuclear analysis. By transforming raw input data into calibrated, labeled spectra with minimal user interaction, this system presents a practical and scalable solution for gamma spectrometry tasks. These results underscore the potential of deep learning techniques to enhance the efficiency, accuracy, and automation of γ-ray spectrometry, offering scalable solutions for real time nuclear monitoring and environmental radiological assessment.

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