

A desktop application for automatic gamma spectroscopy analysis with deep learning

André Gomes Lamas Otero¹, Ademar José Potiens Júnior¹, Juliana dos Santos Lino¹, Julio Takehiro Marumo¹

¹ aglotero@usp.br, Instituto de Pesquisas Energéticas e Nucleares (IPEN / CNEN - SP) Av. Professor Lineu Prestes 2242 05508-000 São Paulo, SP

1. Introduction

In this work, we present a desktop application for automatic gamma spectroscopy analysis with deep learning. This work is focused on the ten most common radionuclides at the IPEN's Radioactive Waste Management Department, SEGRR. A machine learning model was trained with simulated data. The model is based on VGG-19 deep learning architecture, initially used for image classification.

The gamma spectra were generated using Monte Carlo simulation using PENELOPE/PenEasy, simulating an HPGe detector with the sources inside a steel drum filled with paper, in a total of 600 simulations. The data set was enlarged, mixing these simulations into new spectra containing up to four radionuclides. Several distances from the detector to the drum were used (41 cm, 46 cm, 51 cm, and 56 cm) to create a representative data set. The data from 56 cm (originally 150 spectra after the argumentation process 375 spectra) was used for validation purposes.

The model is capable of identifying which radionuclide is present in each spectrum and the current activity of each radionuclide. Then a desktop application was built to use the model, receiving as input the spectrum file and outputting the analysis.

2. Methodology

The PENELOPE/PenEasy Monte Carlo[1] software suite was used to simulate spectra in slightly different geometries. The base geometry consists of a) steel (ASTM A366 1008 alloy with a density of 7.68 g/c³) drum filled with paper (density of 1.2 g/c^3); b) a source positioned inside and at the middle of the drum; c) an HPGe detector.

The simulation and geometry parameters have the ten different radionuclides (Am-241, Ba-133, Cd-109, Co-57, Co-60, Cs-137, Eu-152, Mn-54, Na-24, Pb-210), four different detector-to-drum distances (41 cm, 46 cm, 51 cm, and 56 cm), five multi-channel energy start (0.01 eV, 5 eV, 10 eV, 30 eV, and 40 eV), and three different number of stories to be simulated (1.0e07, 1.0e08 and 1.0e09), resulting in 600 simulated spectra.

These simulation parameters mimic the physical setup of the Ipen's Radioactive Waste Management Department. The Monte Carlo simulation allows only one source per simulation, to train and test with several radionuclides in one spectrum; the data set was enlarged, combining different spectra into a new one.

The model was built using Keras[2] with Tensorflow[3] and the desktop application was built using Python[4] programming language.

The model outputs the probability of a radionuclide exist in the input spectrum and the corresponding activity, measured in Becquerel. The classification part of the model is based on previous work[5] and the corresponding activity is an addition built in this work.

3. Results and Discussion

After 27 epochs of training, the classification accuracy and mean activity squared error reached the best possible values: higher accuracy with lower activity mean square error.

The loss and accuracy, Figure 1, show a steady improvement epoch after epoch.



Figure 1: Model accuracy during training, train, and test data set.

Figure 2 shows the mean absolute error for activity estimation.



Figure 2: Model activity mean absolute during training, train, and test data set.

Figure 3 shows the desktop application interface, the software is ready to receive a gamma spectrum to perform the analysis.

Figure 4 shows the desktop application interface, after performing one gamma spectrum analysis.



Figure 3: Application ready to perform an analysis



Figure 4: Analysis output

The dataset was generated with several geometry configurations, allowing the model to generalize well to the real data acquired at the SEGRR lab from the triple calibration sealed source.

4. Conclusions

The model is capable of identifying the nuclides and estimate their correspondent activities. This application can be used at SEGRR to speed up the drum analysis that is performed in the daily operation routine.

Acknowledgments

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001".

References

- [1] Sempau, Josep. PENELOPE/penEasy User Manual. Version 2019-01-01 (2019).
- [2] Chollet, Francois, *Deep Learning with Python*, Manning Publications (2017).
- [3] Abadi, Martín et al, "Tensorflow: A system for large-scale machine learning", 2th {USENIX}

symposium on operating systems design and implementation ({OSDI} 16), p. 265-283 (2016).

[4] LUBANOVIC, Bill., *Introducing Python: Modern Computing in Simple Packages.*, O'Reilly Media, Inc. (2014).

[5] OTERO, André Gomes Lamas; JUNIOR, Ademar Potiens; MARUMO, Júlio Takehiro,

"Comparing deep learning architectures on gamma-spectroscopy analysis for nuclear waste characterization", *Brazilian Journal of Radiation Sciences*, v. 9, n. 1A (2021).