A desktop application for automatic gamma spectroscopy analysis with deep learning

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Introduction

Neural networks, particularly deep neural networks[1], are used nowadays with great success in several tasks, such as image classification[2], image segmentation[3], translation[4], text to speech[5], speech to text[6], achieving super-human performance.

Previous work investigates the properties of neural networks on gamma-spectroscopy characterization, using different input methods: reducing the input size by averaging ten by then channel[7], identifying the peaks on the spectra to use as input[8] and K-L transformation (a kind of signal compression technique) on the input spectrum[9]. Newest work[10] uses a neural network with all 1014 channel data.

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.

Methodology

The PENELOPE/PenEasy Monte Carlo[11] 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/c³); b) a source positioned inside and at the middle of the drum; c) an HPGe detector with 16384 channels multichannel.

The 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 deep learning model was built using Keras[12] with Tensorflow[13] and the desktop application was built using Python[14] 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[15] and the corresponding activity is an addition built in this work.

Results

After 27 epochs of training, the classification accuracy and activity mean squared error reached the best possible values: higher accuracy with lower activity mean absolute error as shown in Figure 1.

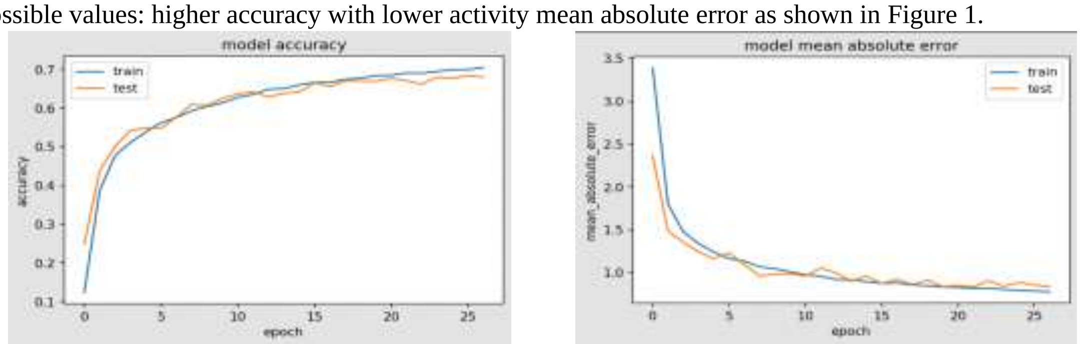

Figure 1: Model metrics during training.

The desktop application used to analyze the IEC files is showed at Figure 3.

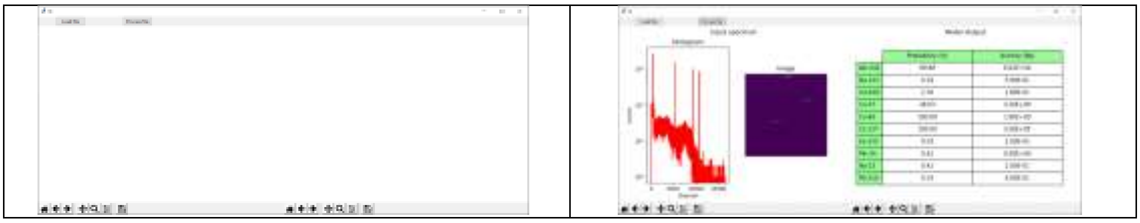

Figure 3: Application when started and after an analysis.

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.

References

1. Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436

2. K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, arXiv preprint arXiv:1409.1556 (2013. K. He, G. Gkioxari, P. Doll´ar, R. Girshick, Mask r-cnn, in: Proceedings of the IEEE international conference on computer vision, 2017, pp. 2961–2969.

4. N. Kalchbrenner, L. Espeholt, K. Simonyan, A. v. d. Oord, A. Graves, K. Kavukcuoglu, Neural machine translation in linear time, arXiv preprint arXiv:1610.10099 (2016)

5. A. Graves, N. Jaitly, Towards end-to-end speech recognition with recurrent neural networks, in: International conference on machine learning, 2014, pp. 1764–1772

6. C. Chiu, T. N. Sainath, Y. Wu, R. Prabhavalkar, P. Nguyen, Z. Chen, A. Kannan, R. J. Weiss, K. Rao, K. Gonina, N. Jaitly, B. Li, J. Chorowski,M. Bacchiani, State-of-the-art speech recognition with sequence-to-sequence models, CoRR abs/1712.01769 (2017). URL: http://arxiv.org/abs/1712.01769. arXiv:1712.01769

7. P. E. Keller, L. J. Kangas, G. L. Troyer, S. Hashem, R. T. Kouzes, Nuclear spectral analysis via artificial neural networks for waste handling, IEEE transactions on nuclear science 42 (1995) 709–715

8. E. Yoshida, K. Shizuma, S. Endo, T. Oka, Application of neural networks for the analysis of gamma-ray spectra measured with a Ge spectrometer, Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment (2002)

9. L. Chen, Y.-X. Wei, Nuclide identification algorithm based on k–l transform and neural networks, Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment 598 (2009) 450 – 453

10. M. Kamuda, C. J. Sullivan, An automated isotope identification and quantification algorithm for isotope mixtures in low-resolution gamma-ray spectra, Radiation Physics and Chemistry 155 (2019) 281–2

11. Sempau, Josep. PENELOPE/penEasy User Manual. Version 2019-01-01 (2019).

12. Chollet, Francois, Deep Learning with Python, Manning Publications (2017).

13. 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).

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

15. 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).