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Highly accurate prediction of specific activity using deep learning

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HIGHLIGHTS

- Traditional method for spectral analysis of material samples is by a HPGe detector.
- The specific activity is processed from spectra to calculate the NORM in Bq/Kg.
- A new method that pre-processes the raw spectrum to feed them into a set of pre-trained neural networks program.
- The pre-trained neural networks program was aim to generate the required specific radionuclide activity.
- Separation of the training process into three neural-networks has improved the prediction results.

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ABSTRACT

Building materials can contain elevated levels of naturally occurring radioactive materials (NORM), in particular Ra-226, Th-232 and K-40. Safety standards, such as IAEA Safety Standards Series No. GSR Part 3, dictate particular activities that must be fulfilled to ensure adequate safety. Traditional methods include spectral analysis of material samples measured by a HPGe detector then processed to calculate the specific activity of the NORM in Bq/Kg with 1.96 σ uncertainty.

This paper describes a new method that pre-processes the raw spectrum then feeds the result into a set of pre-trained neural networks, thus generating the required specific radionuclide activity as well as the 1.96 σ uncertainty.

1. Introduction

Cement manufacturers as well as other building material vendors are obligated to perform γ radiation measurements on randomly selected material samples. Accordingly, classification of materials into three categories is based on the activity concentration index approach (ACI), adopted throughout Europe (NORM IV, 2016):

$ACI < 0.5\ mSv/year$; unrestricted use
$0.5\ mSv/y \le ACI < 1\ mSv/y$; restricted use
$ACI \ge 1\ mSv/y$; prohibited use

The ACI is calculated as follows from Radiological Protection Principles Concerning the Natural Radioactivity of Building Materials, European Commission (1999):

$$ACI = \frac{C_{Ra}}{300Bq \bullet Kg^{-1}} + \frac{C_{Th}}{200Bq \bullet Kg^{-1}} + \frac{C_K}{3000Bq \bullet Kg^{-1}} \quad (1)$$

Where, C_{Ra}, C_{Th}, C_K represent Ra^{226}, Th^{232} and K^{40} activity concentrations, or specific activity, in the building material.

In particular, the specific activities of radio-nuclides are obtained by the following equation (Asaduzzaman and Amin, 2015):

$$A = \frac{N \times 1000}{\varepsilon_\gamma \times \rho_\gamma \times T_s \times M_s} \quad (2)$$

Where, A is the specific activity in Bq/Kg; N represents the net number of counts in the resulting photo-peak; ε_γ is the efficiency of the detector at the corresponding gamma ray energy; ρ_γ is the number of gammas per disintegration of current radionuclide at the specific gamma-ray energy, T_S is the sample counting live-time (seconds) and M_S is the sample's mass (grams).

The gamma spectrometry was obtained as suggested by Levinson et al. (2014): an HPGe detector (EG & G Ortec) system with 20% efficiency (relative to 3″ × 3″ NaI(Tl) at 1332 keV) by which samples were measured in Marinelli beakers.

In order to ensure the equilibrium of Rn^{222} and its daughters in the Ra^{226} chain, a waiting period of at least 21 days was implemented before measurements were taken.

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The specific activity calculation process is as follows:

1. Calibrate system in accordance with a known source to receive an energy dependent efficiency graph
2. Obtain a sample's spectrum using the calibrated system
3. Subtract the background from a sample's spectrum
4. Identify the prominent NORM energy peaks
5. Subtract the trapeze under selected peaks to receive the peaks' net counts
6. Divide the result by the measurement Live-Time to receive counts-*per*-second (CPS)

A peak's activity in disintegrations per second (DPS) is:

$$[dps] = [cps]\frac{100}{Efficiency(E)} \times \frac{100}{RadioNuclideyield(E)}$$

7. Repeat phases 6 and 7 for all selected peaks
8. The result is divided by the sample mass

Specific activity calculations involve correction due to the contribution of other radionuclides. For example, in the case of K-40 the 1459.2 keV peak of the Th-232 daughter, Ac-228, overlaps with the 1460.8 keV peak of K-40, while Ra-226 and Th-232 activity calculations involve the weighted mean value of their daughters in secular equilibrium (Turhan and Gunduz, 2008).

For academic reasons, other methods for calculating the specific activity, such as the Monte Carlo code MCNP, were suggested (Tzortis et al., 2003). In this work, we decided to focus on the performance of artificial intelligence (AI) in the specific-activities evaluation process.

The incentive to investigate the feasibility of this idea came after watching the overlapping spectra graphs (Fig. 1) from which, intuitively, an expert system could extract the specific activity from preliminary knowledge about the spectra measurement live-time as well as the sample's mass and the area under the energy peaks.

As a heuristic example for understanding how an artificial neural networks (ANNs) works, let us take an infant trying to learn the concept of a pencil. By showing him a set of different pencils (colors, sizes, etc.) and pointing out the features common amongst them, he will learn so that, consequently, when presented with a new pencil (one slightly different from the training set), he will be able to identify it with certainty as a pencil.

ANNs were first presented in 1943 by Warren Mc-Culloch and Walter Pitts (Mc-Culloch and Pitts, 1943) as a computational model for neural networks, as an attempt to mimic the learning mechanism of the human brain (Fig. 2).

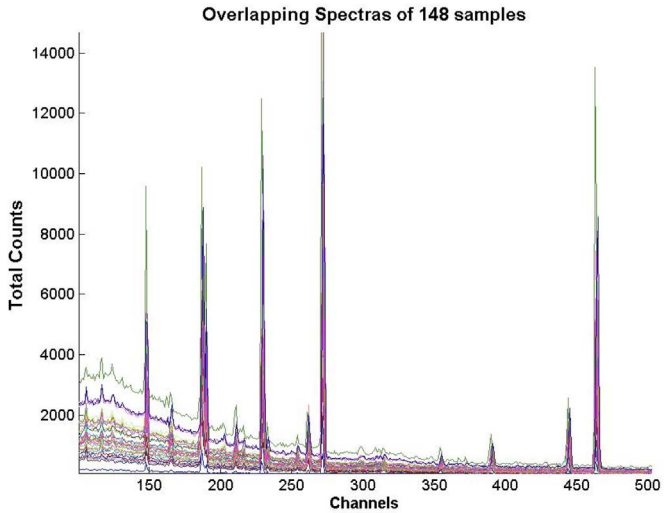

Fig. 1. Overlapped spectra demonstrate resemblance to one another, hence the feasibility of a neural network predictive system.

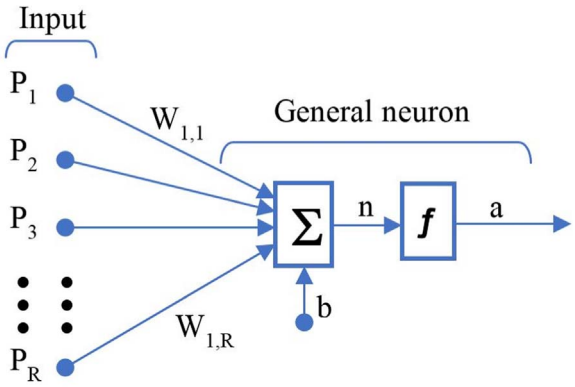

Fig. 2. An elementary neuron with R inputs.

The elementary neuron is simulated by a model such as (can be found in Matlab website: https://www.mathworks.com/help/nnet/ug/neuron-model.html?requestedDomain=www.mathworks.com):

Where,

P - An input vector of R elements.
b - the neuron's bias
f - usually a nonlinear function, such as
Log-Sigmoid $\left(\text{logsig}(n) = \frac{1}{(1+e^{-n})}\right)$ or
Tan-Sigmoid $\left(\text{tansig}(n) = \frac{2}{(1+e^{-2n})} - 1\right)$

a – the neuron's output calculated as:

$$a = f\left(\sum_{i=1}^{R} W_{1,i} + b\right) \quad (3)$$

One popular way to depict an ANN is shown in Fig. 3.

A deep neural network (DNN) is an artificial neural network (ANN) with multiple hidden layers of neurons between the input and output layers (Schmidhuber, 2015). It has been proved empirically that DNN's performance is superior to that of a single hidden layered NN, a claim substantiated by its adoption by leading companies, including Google (e.g., DeepMind; Cloud machine learning services; DeepDream (Mordvintsev et al., 2015)) and Facebook (e.g., Deep-Text, its text understanding engine; DeepFace, a facial recognition application; targeted

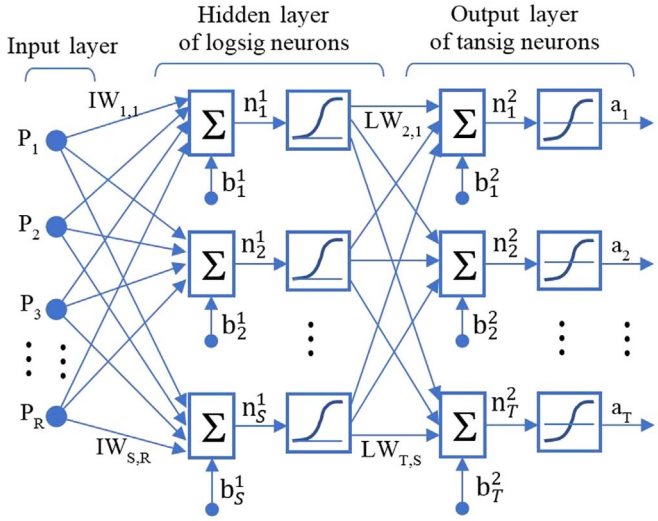

Fig. 3. Typical ANN with R inputs, S neurons in the hidden layer and T neurons in the output layer.