

A Comparison of Machine Learning Methods for Automated Gamma-ray Spectroscopy

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Goals and Objectives

- Main goal: develop a radioisotope identification algorithm that can operate in a wide range of **radiation background fields** and **detector calibrations**.
- Compare the performance of **fully connected neural networks (FC-NNs)** and **convolutional neural networks (CNNs)**.

Introduction

- An algorithm that can quickly determine the **relative activities** of isotopes in **low-resolution gamma spectra** is needed.
- Machine learning and pattern recognition algorithms might be able to incorporate “**intangibles based on experience**” (Rawool-Sullivan et al., 2010).
- For **low-resolution detectors** it may be more beneficial to use algorithms that leverage more **abstract features** of the spectra, such as the shape of **overlapping peaks** and the **Compton continuum**.
- **FC-NNs do not** assume nearby channels are related, while **CNNs do** assume local channels are related
 - Because of this, **CNNs may operate better than FC-NNs** for automated gamma-ray spectroscopy.

Methodology

- Gamma-ray spectra dataset is simulated using **GADRAS**
 - 29 isotopes based on the **ANSI Standard N42.34-2006**
 - 100,000 spectra **uniformly sampled** over all **1-simplicies**
 - Each spectrum has a **calibration shift** between ± 50 channels for a 661 keV photopeak
 - Each spectrum has **random contributions** from background uranium, thorium, and potassium
- Dataset is used to train a **mixture density bagged FC-NN** and a **CNN** to calculate **mixing coefficients** for each isotope in a given spectrum
 - An isotope **mixing coefficient** represents the percent of counts in a spectrum attributable to that isotope

Results

- For each isotope, 100 spectra are simulated for different **source-to-total count ratios**
- Each spectrum has:
 - Random **background isotope contributions**
 - Random **calibration shift**
- **Predicted mixing coefficient** are compared using box-and-whisker plots
 - An ideal 45° dotted line included in each plot

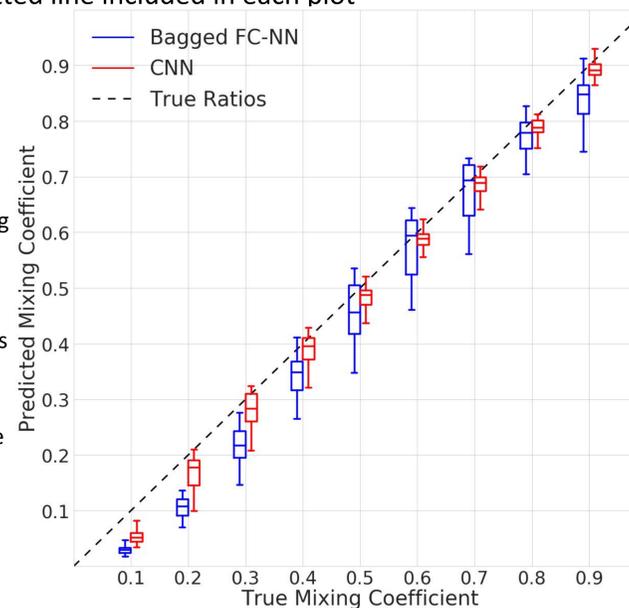


Figure 1. Predicted mixing coefficient for the FC-NN (blue) and CNN (red), averaged over all library isotopes. The total counts in each spectrum is 10^3 . Each spectrum is simulated using the same template as the training dataset.

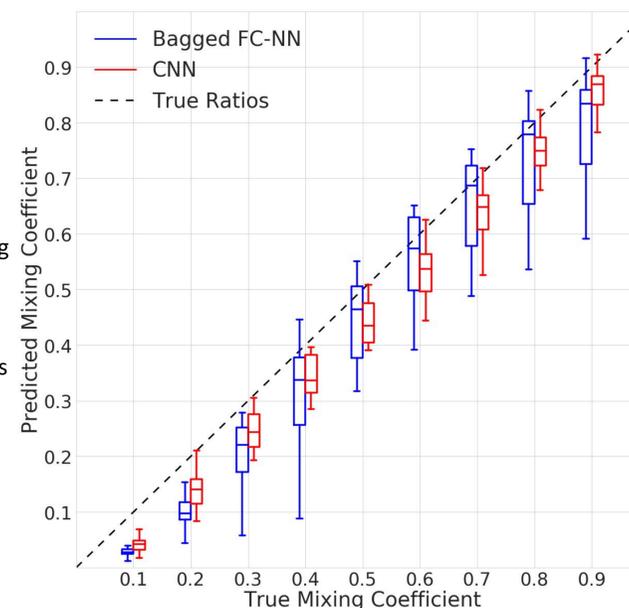


Figure 2. Predicted mixing coefficient for the FC-NN (blue) and CNN (red), averaged over all library isotopes. The total counts in each spectrum is 10^5 . Each spectrum is generated using templates with a wider FWHM than the training dataset.

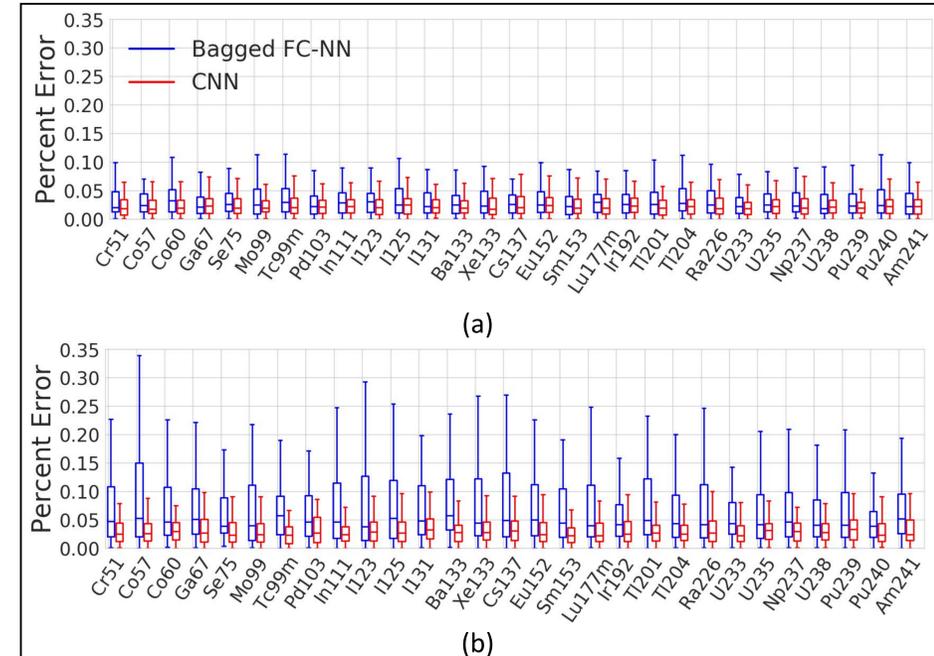


Figure 3. Distribution of the error from the FC-NN (blue) and CNN (red) for each isotope. Each isotope in this dataset was simulated 100 times. Each spectrum in (a) contains 10^3 counts and each spectrum in (b) contains 10^5 counts. For each spectrum, 90% of the total counts are from the source and 10% are randomly generated background.

Discussion

- Both the FC-NN and CNN operated well despite changes in calibration and background radiation field
- The CNN displayed a **similar accuracy** and a **lower variance** for each dataset
- As seen in Figure 3,
 - The CNN **generalized better** to spectra with a smaller number of total counts.

Conclusion

- The CNN performed better overall
 - In general, the CNN was **similarly accurate** and had **less varied outputs** when compared to the bagged FC-NN.
 - Adding **additional detector models** to the training set may improve the performance of CNNs.
- Future work
 - Incorporate **shielding effects**
 - Investigate FC-NNs and CNNs for **uranium enrichment measurements**

