A Machine Learning Approach to Identifying Shielded Radioisotopes in Gamma-Ray Spectra

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Goals and Objectives

- Main goal: Develop NaI-based radioisotope identification algorithms that can identify sources in unknown **shielding configurations, radiation background fields**, and **detector calibrations**

Introduction

- 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**.
- **Dense neural networks (DNNs) do not** assume nearby channels are related, while **convolution neural networks (CNNs) do** assume local channels are related
  - Because of this, **CNNs may operate better than DNNs** for automated gamma-ray spectroscopy
- **Dimension reduction** techniques such as **principle component analysis (PCA)** prevents model overfitting by limiting free parameters

Methodology

- Gamma-ray spectrum templates were simulated using **GADRAS**
  - 29 isotopes based on the **ANSI Standard N42.34-2006**
  - Spectra were simulated with linear **calibration shifts** within ±15 channels for a 661 keV photopeak
  - **Shielding** materials and thicknesses included are listed below
    - Materials correspond to 20%, 40%, and 60% attenuation for a 662 keV photopeak
- Templates were then used to train a classification DNN, PCA->DNN, and CNN

	Material Thickness [cm]		
Aluminum	2.3	4.1	7.2
Iron	0.87	1.6	2.8
Lead	0.42	0.76	1.3

Results

- Weighted F1 scores were compared for simulated spectra
  - F1 score conveys accuracy (1 = perfect, 0 = worst)
- Spectra were simulated with
  - A different background distribution than the one used in training
  - No calibration shift
  - 0.76 cm lead shielding, where indicated
  - All isotopes in training library

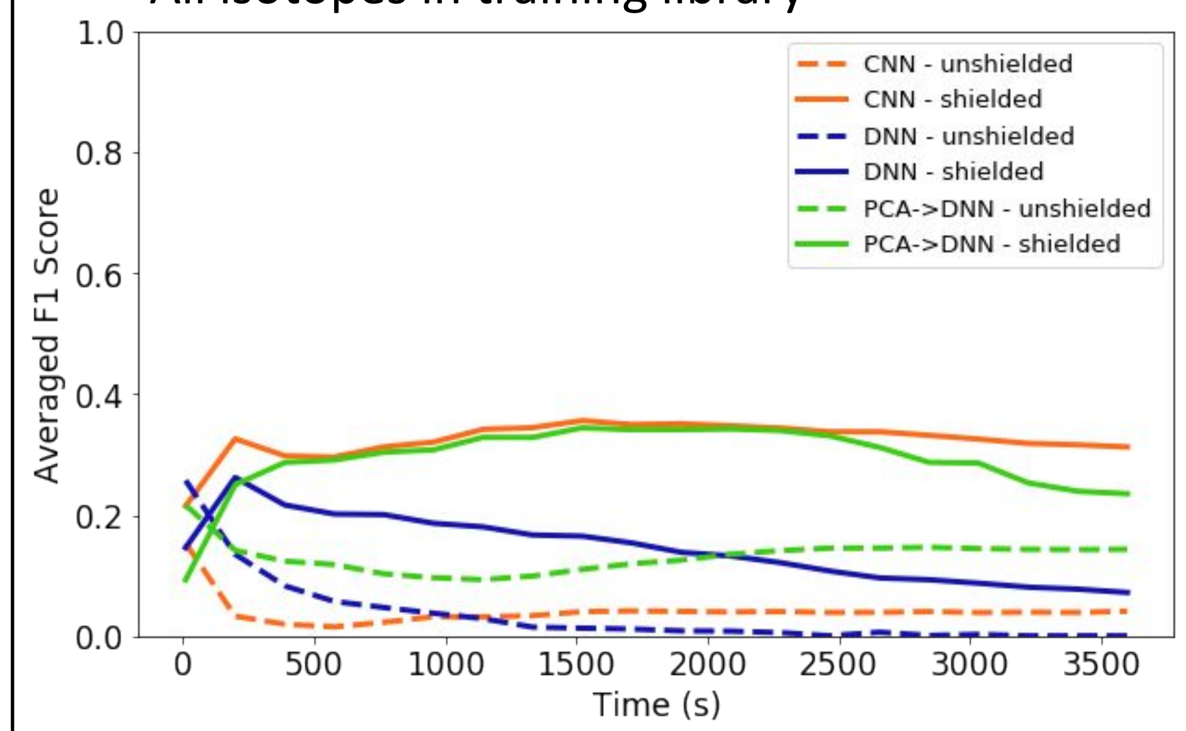

Figure 1. Signal to background ratio set to 1/10.

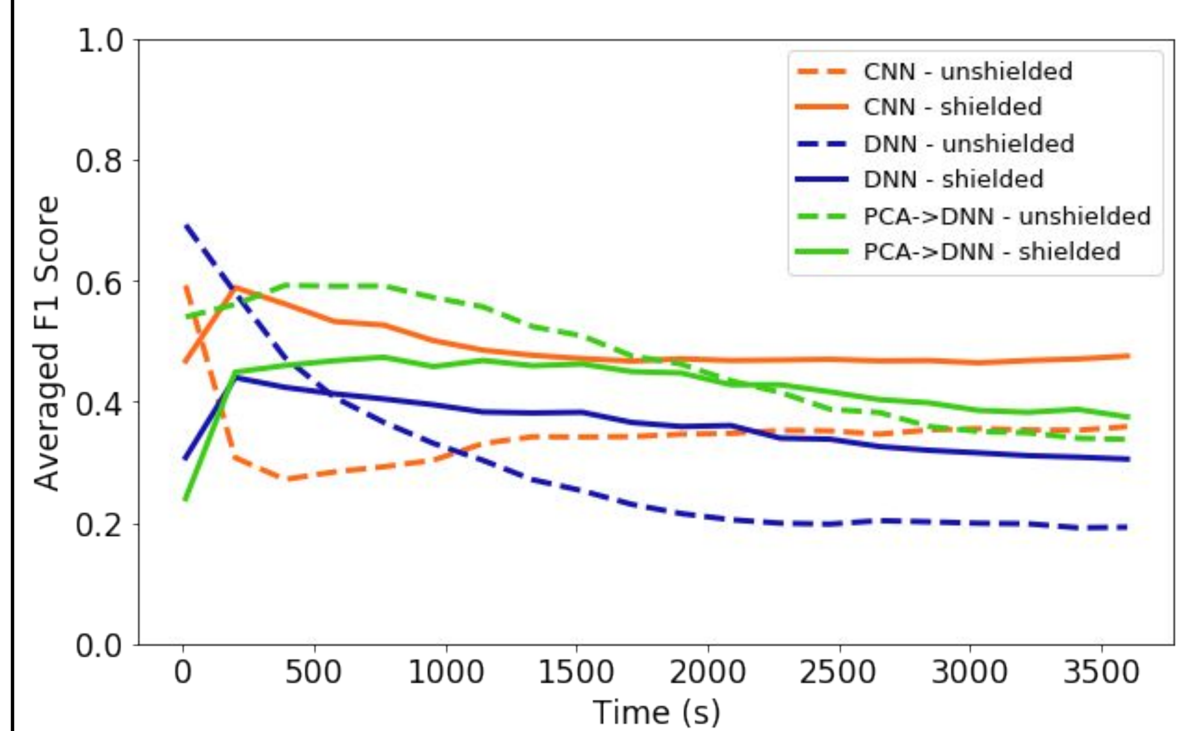

Figure 2. Signal to background ratio set to 1/4.

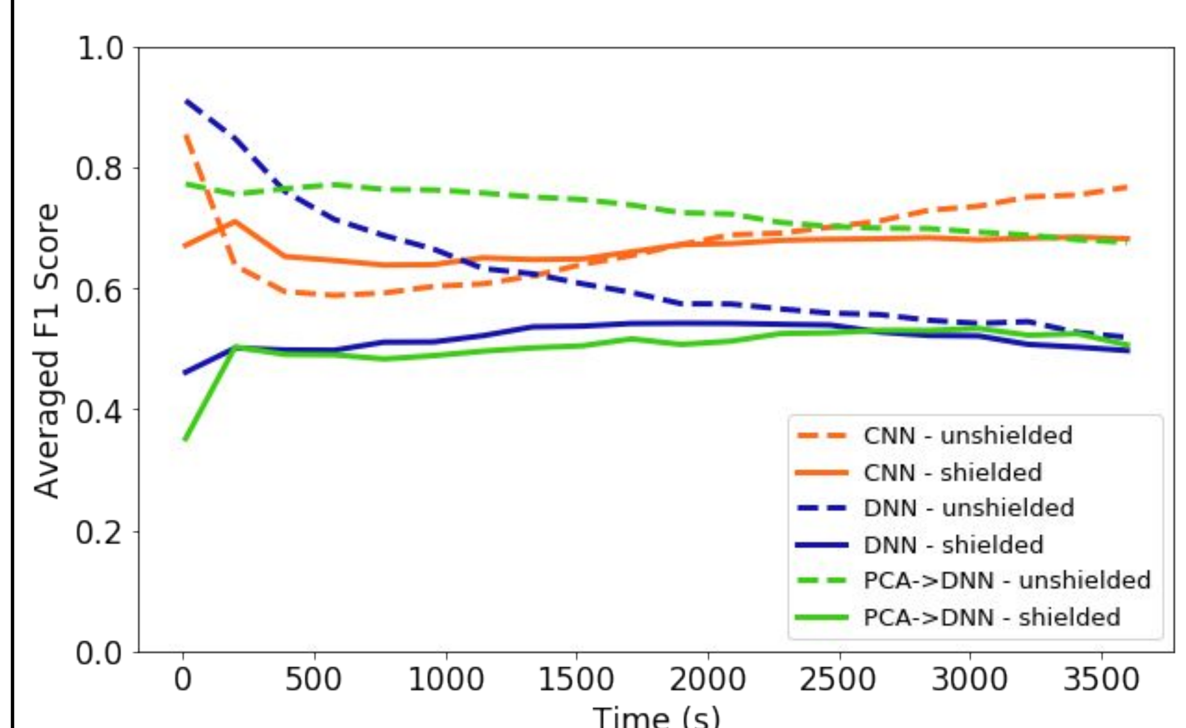

Figure 3. Signal to background ratio set to 1/2.

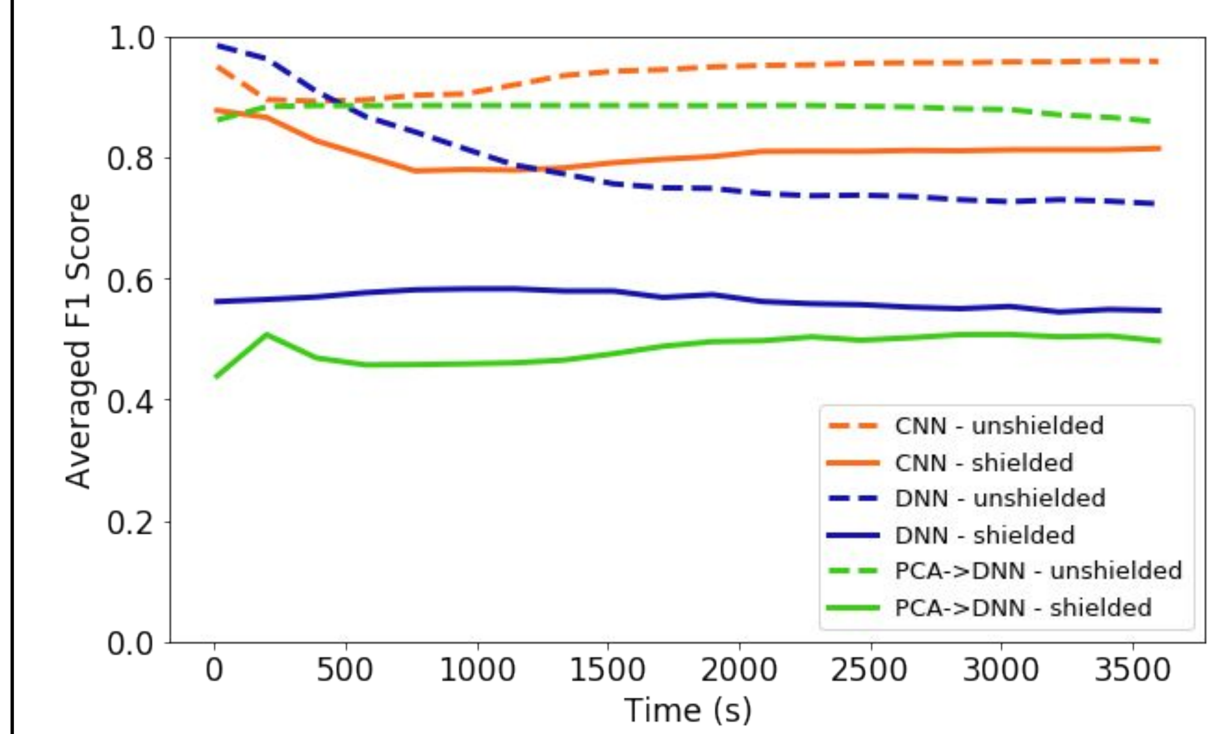

Figure 4. Signal to background ratio set to 1.5.

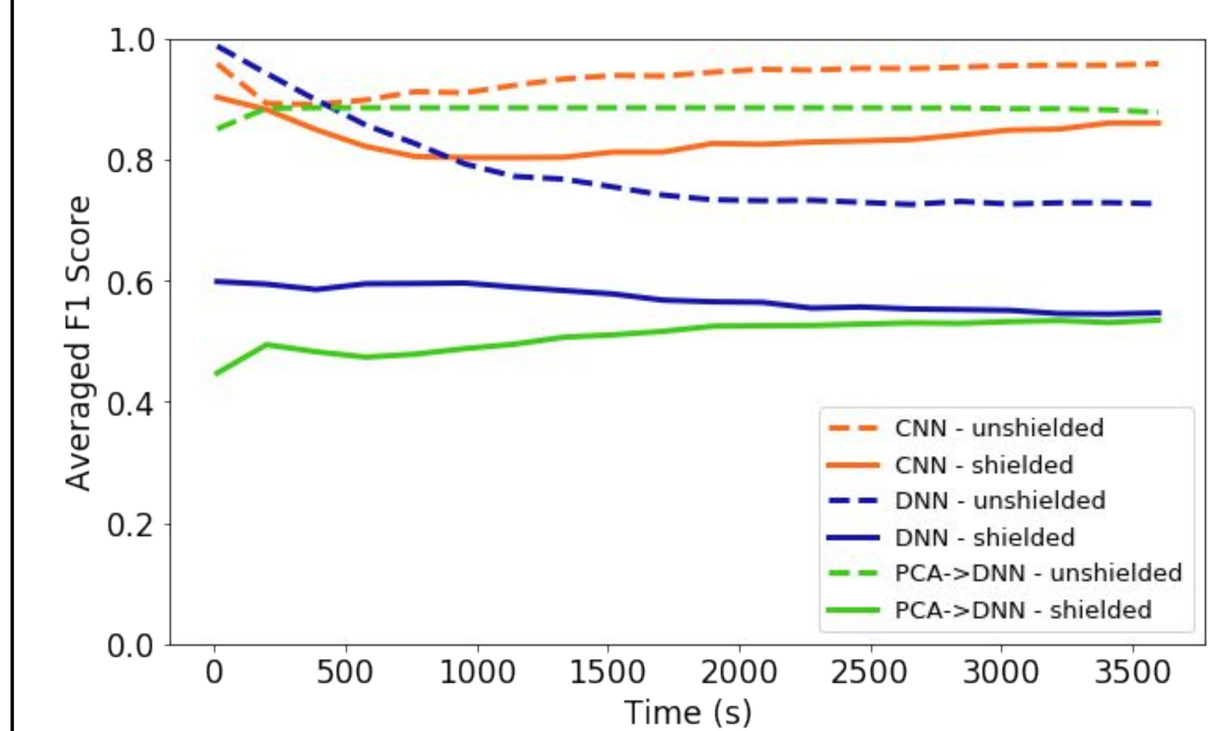

Figure 5. Signal to background ratio set to 2.

Discussion

- The CNN consistently **outperformed** both DNNs on simulated shielded spectra (Figs 1-5).
- The DNN and PCA->DNN both generally performed **worse** with **increased integration time**
- Between a signal to background ratio of 1.5 and 2.0 **performance plateaus**

Conclusion

- The CNN's performance was most promising, **consistent with previous findings** (Kamuda, Zhao, Huff, 2018)
- Future work
  - Investigate different output structures
    - Unshielded & lightly shielded, medium shielding, heavy shielding
  - Explore **unsupervised feature extraction**
    - Background subtracting convolutional autoencoder
  - Investigate performance on real gamma-ray spectra

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