Machine Learning for Smart Space Based Radiation Sensors

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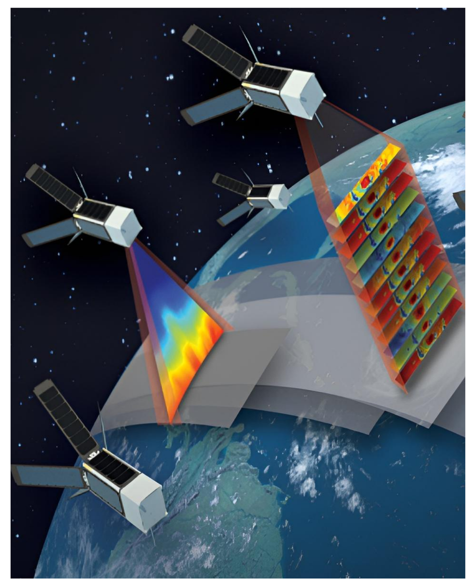
Abstract

- NASA JPL plans to launch MicroRAD, a radiation detector that characterizes the radiation environment and detects energetic particles on a CubeSat in 2024.
- Fluctuations or radiation interactions can cause MicroRAD to output inaccurate data. JPL seeks an autonomous machine learning solution to automate validation and recalibration.
- The algorithm produced assesses data reliability and reproducibility, reducing manual intervention.
- Nominal Low Earth Orbit (LEO) characteristics calibrate the sensor and detect anomalies before reaching the ground team.

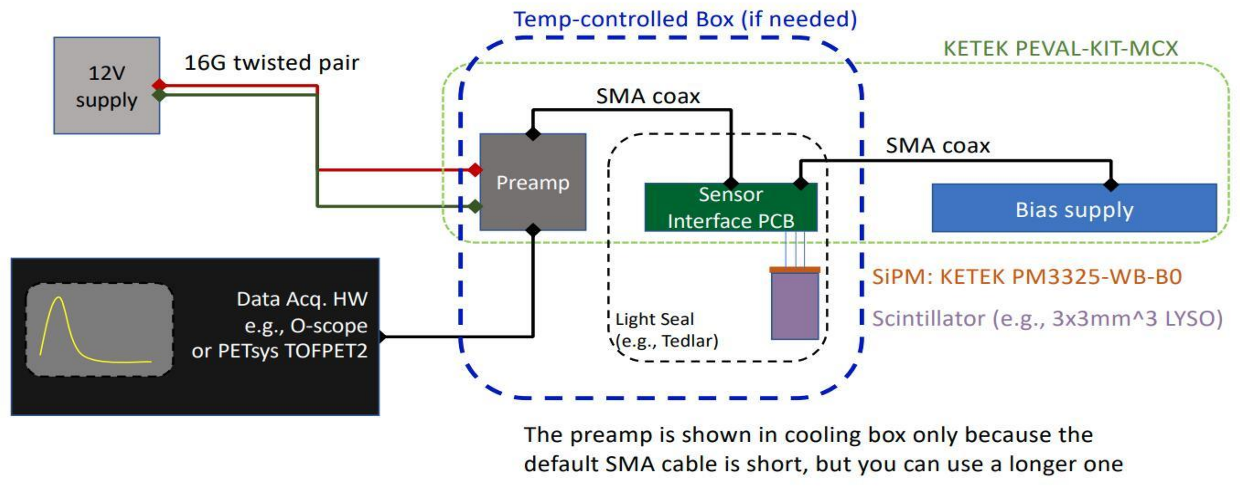


Pre-project Requirements

- For this project to begin, the team had to source a sensor that had comparable specifications to MicroRAD, this included:
  - Crystal scintillator • Power supply • Bias supply • Pre-amplifier
  - Sensor Interface • Data acquisition hardware and software
- The group acquired equipment from the University of Washington to create data sets and optimize the machine learning model's performance on custom hardware, making it adaptable to various radiation sensors.
- The deep learning model needs at least 10,000 readings from each source to be properly trained.

Hardware For Data Collection

In order for our training algorithm to learn how to evaluate incoming gamma ray ions, we were required to collect in-house radiation data using different radiation sources.
The following image describes our data acquisition testbench that was used to record radiation data for Tc-99m, Na-22, Lu-176 and Cs-137.



Hardware For Data Collection (Continued)

Data collection equipment sourced from UW Radiation Imaging Lab:

- KETEK PEVAL-KIT-MCX evaluation kit
- PM3325-WB-B0 SiPM Silicon Photomultiplier wafer
- Agilent Technologies MSO9404A Oscilloscope

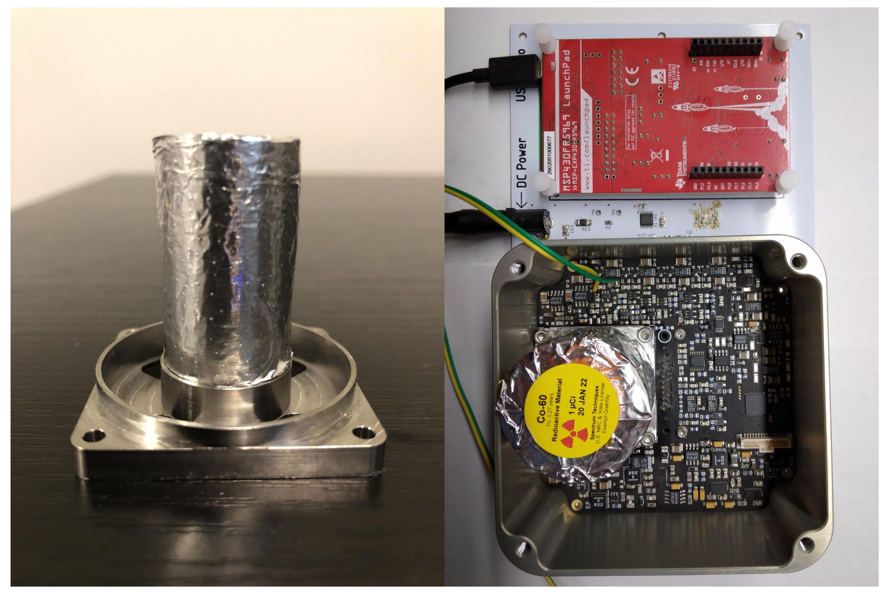
Using this equipment, our group was able to gather over 30,000 data points in the form of radiation pulses that were then pre-processed through our algorithm to extract the necessary information to classify the event as gamma or non-gamma.

Scintillator Hardware

To ensure that our Machine Learning algorithm is able to operate agnostically from the type of radiation sensor, we've constructed our own low-cost plastic scintillator similar to MicroRAD's.

Custom Scintillator Breakdown:

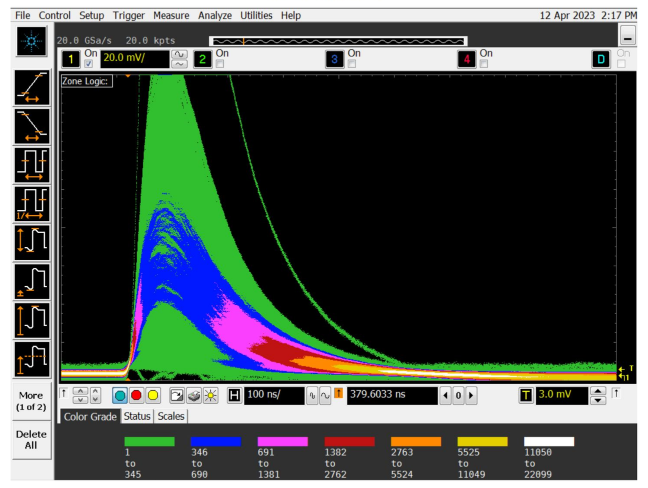
- EJ-276 Plastic scintillator
- Ej-510 Reflective Paint
- Medical Grade Ethanol - 95%
- Fine Grit Sandpaper
- Novus Polishing System
- Aluminum Foil
- Optical Coupling Grease
- Glass Coverslips
- Optical Epoxy



Using our original equipment with our new scintillator, our group was able to create a test set of true gamma and non-gamma ray data. This test set was then used to evaluate the accuracy of our model one again. These results will show that our model was capable of discerning gamma radiation data ranging from 140 KeV to ~1275 KeV.

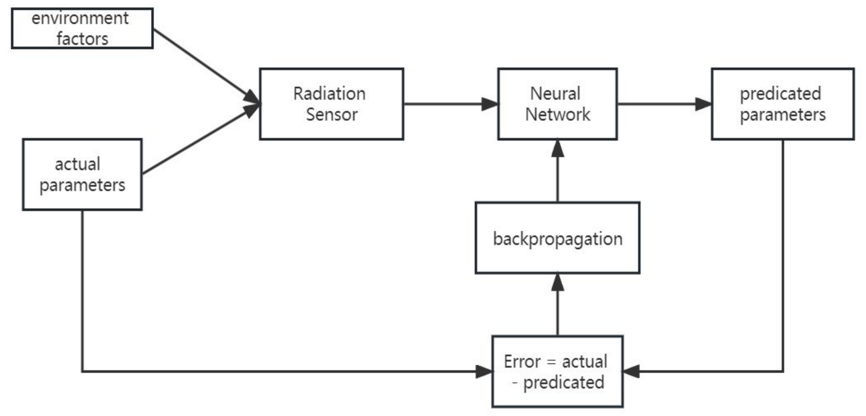
Pre-processing

- Collect reference data of Lu-176, Na-22, Tc-99m and Cs-137 sources.
- The raw data is converted from .bin extension to .csv extension.
- After format conversion, perform integral calculation on each pulse data. Organize the integrals into an order-based data. Find the histogram of the integrals.
- Utilize the peak value of the histogram and documented energy emission levels of radiation sources to establish a linear relationship.
- Employ this linear relationship to predict whether a received radiation event corresponds to a known gamma radiation source.



Machine Learning Plan Overview

- The input data collected from the lab environment and labeled for the neural network.
- After exploring, Once we received all of the data, we settled on building a normal feed forward neural network.
- Model fit different environment parameters for calibration
- Compare the parameters of the radiation sensor and the predicted parameters
- Train the neural network by the predicted and actual calibration parameters



Machine Learning – Calibration Pipeline

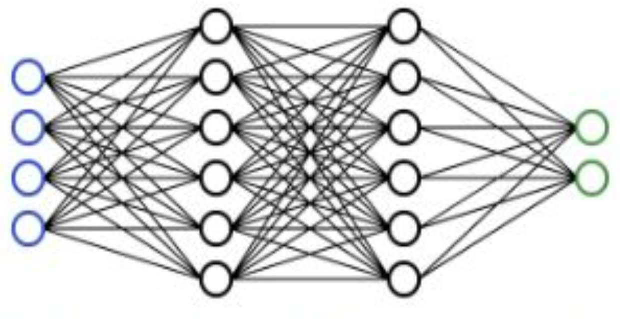
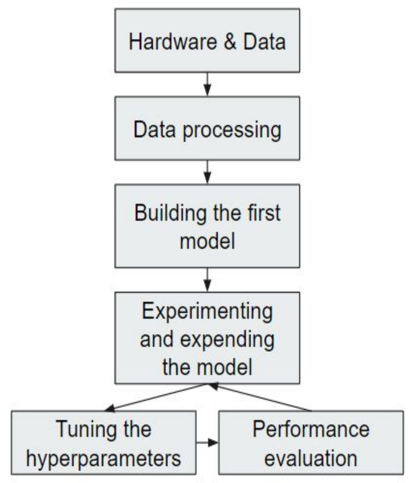


Fig. A Concept Diagram for Neural Network

```
While(True):
    new_data = radiation_sensor(actual_calibration)
    processed_data = preprocess_data(new_data)
    predicted_calibration = nn_model(processed_data)
    error = actual_calibration - predicted_calibration
    error.backpropagation()
    model_parameters = model_parameters
-       learning_rate*derivative_error
```

Machine Learning - Implementation



Plan of experimenting with neural network architectures

- Number of layers: 3, 5, 7, or 9 layers
- Number of neurons per layer: 16, 32, 64, or 128 neurons
- Activation functions: ReLU, sigmoid, or tanh
- Regularization techniques: L1/L2 regularization, dropout, or batch normalization
- Optimization algorithms: Adam, RMSprop
- Loss function: mean squared error (MSE), cross-entropy
- Other hyperparameters: number of epochs, learning rate, dropout rate, or batch size

Results and Future Work

- The model performed with a training accuracy of 0.8 and a validation accuracy of 0.77. Also, the model has training losses of 0.54 and validation losses of 0.45. However, the model did not improve after 100+ epochs (iterations) showing that it was not able to make further connections or relationships amongst our data.
- To further the effectiveness of our model, larger batches of data (+10,000 waveforms) should be used to extract more physical characteristics unique to ionizing radiation to draw more conclusive characterization from the model.
- Physical characteristics that may prove valuable to assess are peak values, integrals, histogram plotting, etc. this information can be used by the model to draw better conclusions on true and false radiation readings.
- In the future, we can change our model to determine other forms of radiation such as alpha, beta, and etc. Also, we can experiment with different machine learning models, architectures, hyper parameters, and augment data to further increase accuracy and decrease computation time.

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