



## Beta-Gamma coincidence radioxenon spectra classification using the convolution neural network (CNN) technique

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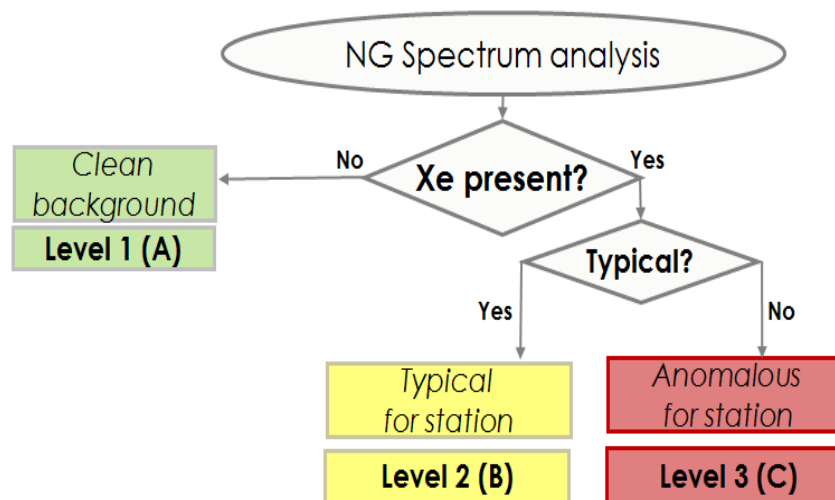
## INTRODUCTION

- International Monitoring Systems (IMS) can detect the amount of radioxenon in the atmosphere by sampling and measuring activity concentrations of  $^{131}\text{mXe}$ ,  $^{133}\text{Xe}$ ,  $^{133}\text{mXe}$ , and  $^{135}\text{Xe}$  in order to identify and prevent any nuclear test explosion.
- Concentrations of approximately 60+ samples are measured every day based on the collection time of three types of radioxenon systems in 12-or 24-hour air samples in completely operational 40 IMS noble gas components.
- Further buildup of the network will also increase the number of samples to be analyzed every day.
- A categorization scheme is needed to screen out samples that are uninteresting in the CTBT context.
- Analysts need to review and screen samples to distinguish subsequent civilian sources from a nuclear explosion.



## INTRODUCTION

Noble Gas is categorized into three levels based on activity concentration levels and long-term trend (365 moving days). Categorization principles have been established in order to classify observed events.





## INTRODUCTION

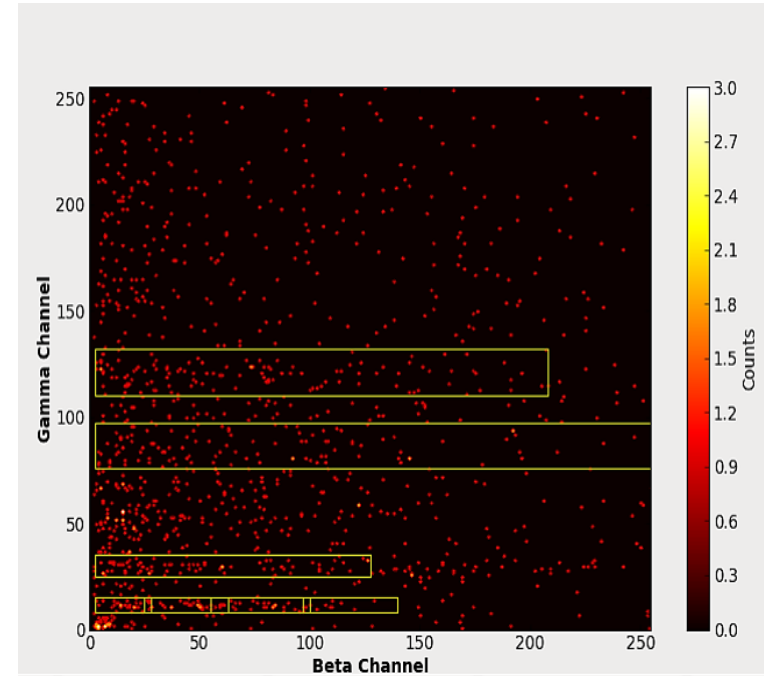
- The analysis method currently employed by the International Data Center (IDC), known as “Net-Count Calculation” (NCC) method.
- Artificial intelligence (AI) has been growing fast with numerous practical applications and active research topics.
- For the first time, we present a machine learning perspective in categorization Beta-Gamma coincidence of radioxenon spectra based on real data.
- ✓ Categorization is important to screen the samples to focus only on the important samples that might be associated with a nuclear explosion.
- ✓ To enhance the automatic processing and keep the workload of analysts of the International Data Centre (IDC) at the current level.
- ✓ To assist the National Data Centers (NDCs) in day-to-day and manual review of samples and identify those significant ones that could possibly be associated with a nuclear explosion.



## METHODOLOGY

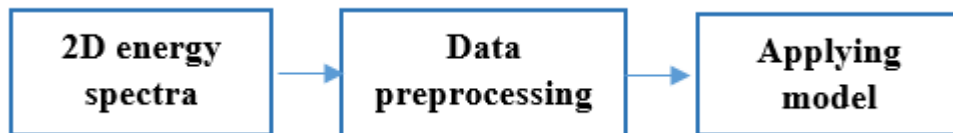
### ➤ Input data

- Real raw data derived randomly from USX75 measurement station (located at NG Charlottesville, USA) between 2012 and 2019.
- The dataset in binary classification, regarding to categorization scheme in slide 3, we combined level two and level three and separated them from level one to detect *background* spectra. The dataset includes 532 raw spectra of level one, 468 spectra of level two samples and 442 samples of level three.
- In atypical detection spectra, we combined level one and level two and separated them from level three to predict whether each sample is *anomalous* for the station or not. The dataset includes 532 raw spectra of level one, 556 spectra of level two samples and 442 samples of level three.

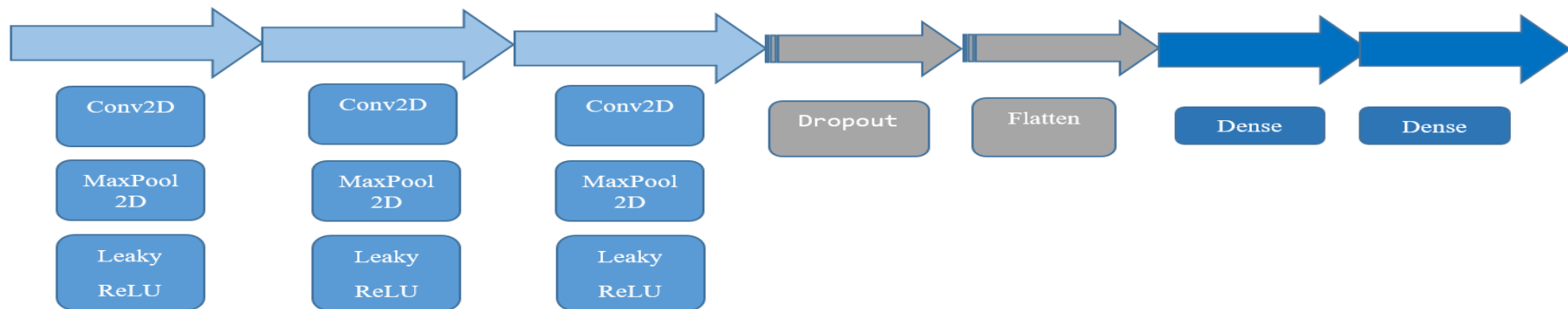


## METHODOLOGY

### ➤ Method



### ➤ Model

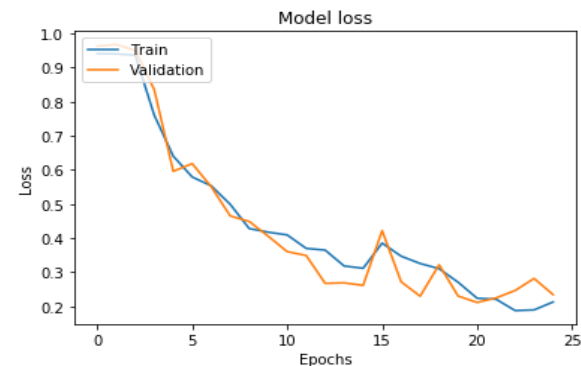
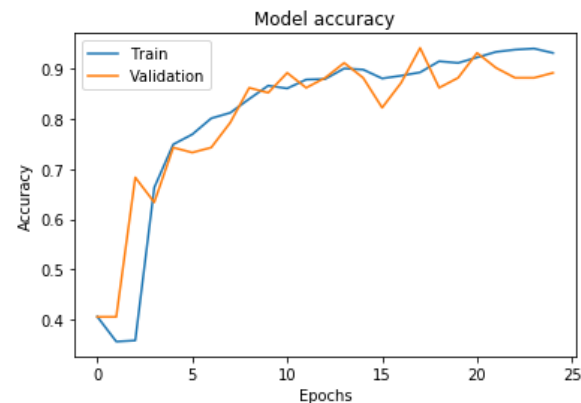


## RESULTS

### ❖ Performance measures for classification of background spectra from other levels

Test data for USX station\_ Binary classification (Background)

Confusion matrix		Actual output		Evaluation parameters			Sensitivity (Average true positive rate)
		Class	Class	precision	recall	f1-score	
		1	2				
Prediction output	Class 1	151	16	0.90	0.90	0.90	0.94
	Class 2	17	249	0.94	0.94	0.94	
Specificity (Average true negative rate)		0.90					overall

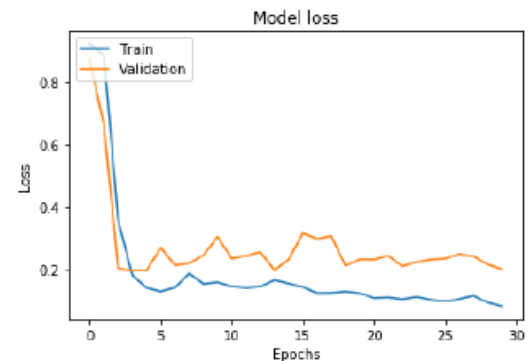
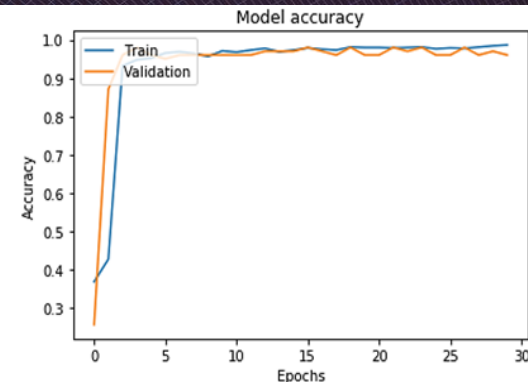


## RESULTS

### ❖ Performance measures for classification of anomalous spectra from other levels

#### Test binary classification (Anomalous)

Confusion Matrix		Actual output		Evaluation parameters			Average sensitivity
		Class 1	Class 2	Precision	Recall	F1-score	
Prediction output	Class 1	311	0	0.97	1	0.99	0.96
	Class 2	9	110	1	0.92	0.96	
Average specificity		0.96					Overall








## CONCLUSION

- ✓ Deep learning model can be utilized as an important pre-screening method to highlight relevant samples prior to their interactive analysis to be used for prioritization of work assignment by analysts.
- ✓ That is possible to use deep learning algorithm to well distinguish anomalous spectra containing large amounts of radioxenon and to detect background spectra by analyzing the entire real raw two-dimensional spectra.
- ✓ The classification analysis can be conducted without needing information such as backgrounds data, interference contributions from other radionuclides, abnormal limit measured for each spectrum, and consecutive isotopes and also calculating activity concentrations.



Thank you for your attention