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Enhancing Multimodal Tomography for Nuclear Applications using Machine Learning

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ABSTRACT:

We will develop methods based on machine learning for upsampling and denoising muon, and gamma tomographic images of spent nuclear fuel casks. Passive radiation such as gamma rays originating from radioactive samples, and naturally occurring probes such as cosmic ray muons can be used for imaging spent nuclear fuel casks. Because external radioactive sources or particle beams are not required, imaging using these types of radiation can be done in a more simple, cost-effective and safe way using detectors. Due to the natural limit of the particle fluxes, however, imaging times can be on the order of days and imaging results are limited in resolution and signal-to-noise ratios. We will develop methods based on machine learning to improve both the resolution and signal-to-noise ratios of passive multimodal tomography images. This work will dramatically enhance the sensitivity of dry cask imaging technologies and directly addresses the Office of Nuclear Energy's Office of Spent Fuel & Waste Science and Technology's mission to "*...provide confidence in the safe long-term management of the nation's spent nuclear fuel... by reducing uncertainty and advancing technology for extended storage...*".

In the proposed work, the project team at the Colorado School of Mines, Los Alamos National Laboratory, and the International Centre for Theoretical Physics will develop and deliver: Training data consisting of cosmic ray muon as well as passive gamma simulations of diverse spent fuel casks; Training data consisting of experimental measurements of muon scattering from surrogate samples; Optimized and validated convolutional neural networks for upsampling and denoising individual and synthesized radiation modes' tomographs; Optimized and validated machine learning models for denoising gamma and muon sources used in tomographic applications.