Muon Tomography for Nuclear Waste Characterization Using Machine Learning

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1 Abstract

Muon tomography, a non-destructive imaging technique, holds significant promise for characterizing nuclear waste containers. This research explores the application of machine learning, specifically convolutional neural networks (CNNs), to enhance the analysis of muon tomography data. The study involves simulating muon interactions with various materials commonly found in nuclear waste containers, incorporating noise and augmentation techniques to mimic real-world conditions. A baseline CNN model is developed and evaluated for material classification. Furthermore, the research investigates the integration of statistical methods, such as Poisson distribution, Markov chain models, and survival analysis, to refine predictions and improve the robustness of the model. The results demonstrate the potential of machine learning, combined with physics-based simulations, to advance the field of nuclear waste characterization, enabling safer and more efficient management of radioactive materials.

2 Introduction

The safe and efficient management of nuclear waste is a critical challenge. Muon tomography, leveraging the penetrating power of cosmic ray muons, offers a non-destructive approach to image the contents of nuclear waste containers. However, analyzing muon tomography data can be complex and time-consuming. This research explores the use of machine learning to automate and enhance this process.

3 Methodology

This research employed a multi-faceted approach, combining data simulation, machine learning, and statistical methods. Initially, synthetic muon tomography data was generated using material densities and incorporating noise to mimic real-world scenarios. A baseline CNN model was then developed and trained for material classification. To enhance the model's robustness and predictive capabilities, the dataset was augmented using Monte Carlo simulations, Poisson distribution, Markov chain models, and survival analysis. These techniques aimed to capture the stochastic nature of muon interactions and the time-dependent properties of radioactive materials. Zonotopic Dempster-Shafer Structures (DSZ) were also investigated for modeling and managing uncertainty in the data. Finally, their performance was tested against deeper and more robust architectures such as the one of GoogleNet. The performance of the models was rigorously evaluated using metrics such as accuracy and loss, and comparisons were made between the baseline and augmented models.

4 Data Simulation and Augmentation

To train and evaluate machine learning models, a dataset of simulated muon interactions with various materials was generated. The materials considered include steel, lead, concrete, water, uranium, plutonium, cesium, and cobalt, reflecting the typical composition of nuclear waste containers. Noise was introduced to the simulated data to mimic real-world measurement uncertainties. Additionally, data augmentation techniques, including Monte Carlo simulations, were employed to increase the dataset size and variability.

5 Baseline CNN Model

A baseline CNN model was developed for material classification. The model consists of two convolutional layers, each followed by max pooling, a flattening layer, a fully connected layer, and a final multi-class classification layer. The model was trained on the simulated dataset and evaluated on a separate test set.

6 Statistical Methods for Enhanced Accuracy

To further improve the model's performance and robustness, statistical methods were integrated into the analysis pipeline. Poisson distribution was used to model the stochastic nature of muon flux measurements. Markov chain models were employed to capture the layered shielding effects and time-dependent decay properties of nuclear waste materials. Survival analysis was applied to simulate the survival times of muons as they traverse different materials, providing time-resolved data for enhanced predictions.

7 Zonotopic Dempster-Shafer Structures (DSZ)

The research also investigated the use of Zonotopic Dempster-Shafer Structures (DSZ) to model and manage uncertainty in muon tomography data. DSZ combines the principles of Dempster-Shafer Theory (DST) with zonotopic representations, offering a robust and flexible way to represent uncertainty, particularly in situations where data is imprecise, incomplete, or conflicting.

8 Results and Comparisons

The performance of the baseline CNN model, augmented with statistical methods and DSZ, was evaluated alongside with their counterparts on GoogleNet architecture. The results in Figure 1 and 2 showed significant improvements in accuracy and robustness compared to the baseline model. The integration of statistical methods and DSZ enabled the model to better handle real-world uncertainties and variations in muon tomography data. Furhtermore, the use of more sophisticated architectures proved a better performance even for noiser data such as the one from survival analysis.

However, more work and improvements could be done since the accuracy is still very low and after several runs, the results of the methods with the simple architecture vary constantly, showing its lack of robustness to challenging data, being this way, the DSZ approach a promising solution delivering always similar results, specially when combined with robust architectures offering a better accuracy, even with a higher loss. Therefore, future research is needed and the implementation of regularization techniques, the comparison with other metrics such as F-1 score and a bigger dataset for training.

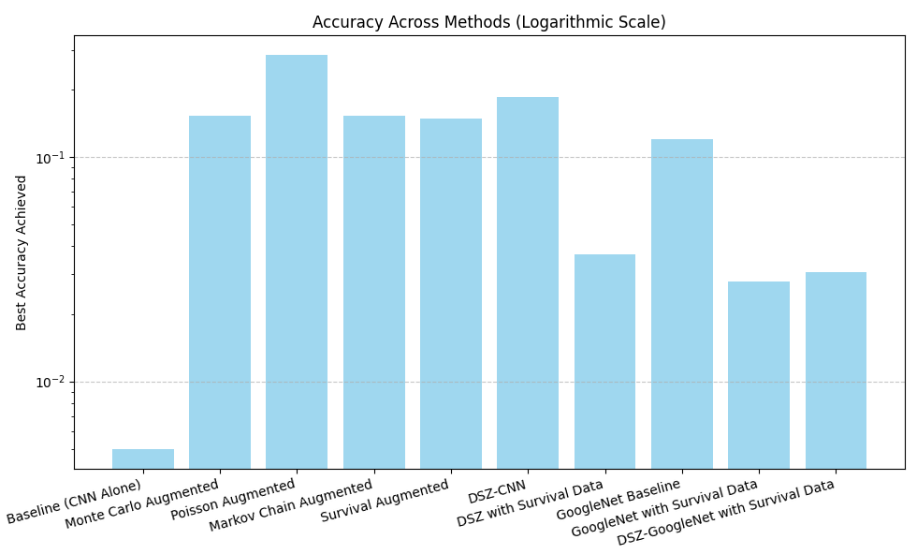

Figure 1: Best accuracy across methods

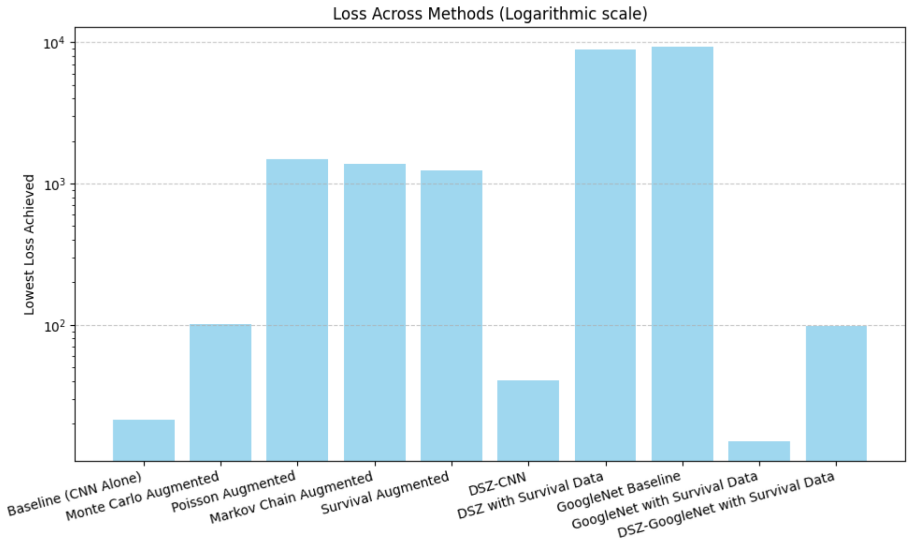

Figure 2: Best loss across methods

9 Conclusion

This research demonstrates the potential of machine learning, combined with physics-based simulations and statistical methods, to advance the field of nuclear waste characterization. The developed models offer a promising approach to automate and enhance the analysis of muon tomography data, enabling safer and more efficient management of radioactive materials. Further research is needed to validate these models on experimental data and explore their application in real-world scenarios.

10 References

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