A Machine Learning-Based Framework for Radiation Transport and Energy-Deposit Classification

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Radiation transport plays a crucial role in a variety of high-energy physics and astrophysics experiments, including space-borne missions aiming to detect cosmic rays or perform gamma-ray spectroscopy [2]. Precise energy-deposit measurements are essential for identifying signals from cosmic events and discerning particle interactions within complex detector systems [1]. Typically, such measurements involve large-scale MC simulations (e.g., *Geant4*, *MCNP6*) to capture scattering, absorption, and pair-production processes [3]. However, these simulations can be computationally expensive when exploring large parameter spaces or enabling real-time event classification.

ML approaches have emerged as powerful tools for extracting patterns from high- dimensional datasets, making them particularly suitable for radiation detection scenarios [4]. Furthermore, novel *physics-informed* techniques allow ML models to incorporate well-established physical laws, ensuring both interpretability and reliability [5]. In this work, we apply these principles to the design and analysis of detectors relevant to ongoing projects such as *NUSES* and *ZIRE*, which seek to measure cosmic-ray fluxes and other high-energy phenomena in challenging environments.

We begin with Geant4-based simulations of charged particles, cosmic-ray secondaries, and gamma rays interacting with various detector materials [1]. We generate a synthetic dataset comprising multiple particle types and energies under different incidence angles, incorporating realistic shielding and environmental parameters (e.g., altitude, atmospheric depth) relevant to NUSES- or ZIRE-like missions.

From the simulation outputs, we extract energy-deposit distributions, pulse-height spectra, and temporal signals. Domain-specific features (e.g., charge drift time, timing coincidence with auxiliary detectors) provide a rich representation of each interaction event. Contextual metadata (e.g., detector temperature, cosmic-ray flux) are also recorded to track environmental variations.

Our hybrid system integrates a feedforward neural network with physics-informed regularizations to preserve fundamental conservation laws and known detector response characteristics. The network is trained on labeled MC data to classify events (e.g., single-particle deposit vs. multi-scattering). We incorporate a loss term that penalizes unphysical solutions (e.g., events with energy sums exceeding the known beam energy), enhancing interpretability and robustness.

Once validated against benchmark simulations, the trained model is deployed to process real-time or near-real-time data. This allows dynamic reconfiguration of operational parameters: for instance, adjusting the trigger threshold based on the local cosmic-ray background observed in suborbital or underground laboratories.

Our approach demonstrates that combining rigorous radiation transport simulations with ML algorithms—and infusing physical constraints into network architectures—can significantly enhance the accuracy of energy-deposit classification for cosmic-ray and gamma-ray detection. This hybrid methodology holds promise for improving the signal-to-background ratio in upcoming experiments, such as NUSES and ZIRÈ, while also offering the potential for real-time data analysis and automated detector optimization. Future efforts will incorporate larger-scale data from flight tests, emphasizing uncertainty quantification, adaptive calibration, and robust performance across variable environmental conditions.

References

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