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We present MaNFRED (Material Neural Field for Radiographic Experimental Diagnostics), a comprehensive AI-driven workflow for reconstructing 3D material properties and physics observables from 2D multi-modal radiographic imaging. The framework addresses the critical challenge in high-temperature plasma diagnostics: inferring volumetric structure from sparse imaging data in precious and costly experiments, enabling spatial analysis previously requiring extensive manual interpretation or impossible with existing methods [3].

Our development pipeline focuses on co-analysis reconstruction and incorporates three key stages: (1) pre-training via simulated radiographs spanning 80-800 MeV proton, 9-20 MeV X-ray, and 1-14 MeV neutron imaging, (2) implicit neural representation (INR) [1,2] extending state-of-the-art 3D reconstruction techniques to predict a continuous field of occupancy, density, and atomic number for an imaged object, and (3) a physics-informed vision transformer to use our material model to predict 2D radiographs. This combined model can be pre-trained on vast in-silico examples and automates co-analysis while increasing material resolution by exploiting complementary material sensitivities across particle species—heavy elements exhibit strong X-ray contrast while low-Z materials are better characterized by neutron imaging.

We present quantitative benchmarks demonstrating automated co-analysis for complex target geometries prohibitive by other methods (e.g. Bayesian Optimization). In addition, we demonstrate reconstruction of simulated ICF hot-spots using pinhole camera radiography. Our complete pipeline (~11.5k lines) runs on existing diagnostic data with no hardware modifications, providing proof-of-concept for extensive automated analysis and laying groundwork for end-to-end capabilities across a wide range of experimental imaging needs.

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