Early-Stage Failure Predictions in Fusion Materials using Machine Learning

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Abstract.
The structural integrity of Plasma-Facing Components (PFCs) and breeder blanket modules represents a primary engineering bottleneck for the realisation of commercial nuclear fusion. During operation, these materials are subjected to unprecedented synergistic loads, including high-energy neutron flux (14.1 MeV), cyclic thermal stresses and high temperatures exceeding $1000°$C. Such conditions induce complex non-linear microstructure evolutions, ranging from dislocation loop formation and void swelling to Radiation-Induced Segregation (RIS), which collectively drives embrittlement and eventual component failure. Traditional analytical methods often fail to predict these catastrophic failure events because the underlying deformation mechanisms interact non-linearly across atomistic, microscopic and macroscopic scales, ways in which are difficult to model deterministically. We propose a data-driven framework to identify early-stage deformation pattern that serve as consistent precursors to material failure.

By applying advanced pattern recognition and machine learning (ML) techniques to large databases of experimental data, this work aims to reveal the latent “fingerprints” of damage that are often hidden within high-noise environments. The methodology focuses on using unsupervised learning and anomaly detection to isolate subtle microstructural shifts before they manifest as macroscopic cracks. This work aims to resolve the long-standing challenge of accurately identifying active slip systems during grain-scale deformation by utilising an integrated input of kinematic Digital Image Correlation (DIC) maps and Euler angle-derived orientation data. By capturing the complex interplay between the local strain localisation and crystallographic constraints, this work establishes an automated pipeline that characterises plastic anisotropy in polycrystalline materials much more effectively than the conventional post-mortem analysis.

The computational core of this framework relies on the high-fidelity fusion of spatial strain distributions and crystallographic orientations, processed across a massive experimental dataset. Specifically, this study utilises over 1000 individual kinematic DIC maps captured at high temporal resolution, paired with corresponding Electron Backscatter Diffraction (EBSD) orientation datasets. This high-volume image library provides a high-resolution representation of local displacement gradients, which are subsequently correlated with grain-level Euler angles to calculate the Critical Resolved Shear Stress (CRSS) and Schmid Factors for all potential slip systems. To process this high-dimensional image data, the pipeline is implemented within the PyTorch ecosystem, leveraging its dynamic computational graphs for efficient gradient flow during model optimisation. The primary architecture consists of a Deep Residual Network, specifically chosen for its ability to mitigate the vanishing gradient problem through identity shortcut connections. This architecture is critical for extracting subtle “strain signatures” associated with active vs latent slip planes from the high-noise backgrounds inherent in extreme-environment experimental data.

By employing a hybrid approach that combines supervised classification for known slip modes with unsupervised anomaly detection, the system isolates subtle microstructural shift before they manifest as macroscopic cracks. The PyTorch-driven Residual Network can identify “rogue” deformation patterns, deviations from expected crystallographic behaviour, that signify the onset of radiation-induced damage. This allows the pipeline to differentiate between standard plastic flow and localised strain accumulations indicative of early-stage void formation or dislocation pinning, providing a granular look at the material’s degradation state that traditional bulk mechanical testing cannot achieve.

Ultimately, this research aims to bridge the critical gap between fundamental multiscale physics and experimental observation, facilitating a transition toward proactive structural health monitoring for fusion environments. Identifying these early warning signs is essential for the safe design and optimised operation of next-generation fusion reactors, providing a predictive window that traditional analytical methods currently lack. By revealing these latent fingerprints, this work will enhance the reliability of PFCs and breeder blankets, ensuring they can withstand the unprecedented synergistic loads of the reactor's extreme environments. This data-driven approach offers a scalable solution to the obstacles of material degradation, moving beyond reactive post-mortem analysis toward real-time failure prevention. This is vital for maintaining the structural integrity of the reactor's first wall, where the non-linear interaction of deformation mechanisms determines the viable lifecycle of the entire facility. The integration of machine learning into materials characterisation will not only improve the safety protocols but also accelerate the development of radiation-resilient materials necessary for commercial fusion energy.

Key Words.
Nuclear Fusion, Radiation Damage, HRDIC, Pattern Recognition, Multiscale Deformation, Machine Learning, Residual Networks.