Machine learning enhanced microscopy identification of defects

Nicole Bishop [1,2], K.S. Mao [2,3]
1. Florida State University College of Medicine, Tallahassee, FL 32306,USA.
2. National High Magnetic Field Laboratory, 1800 East Paul Dirac Drive, Tallahassee, FL 32310, USA.
3. Department of Industrial and Manufacturing Engineering, FAMU-FSU College of Engineering, Florida State University, Tallahassee, FL, 32310, USA

Why Machine Learning?

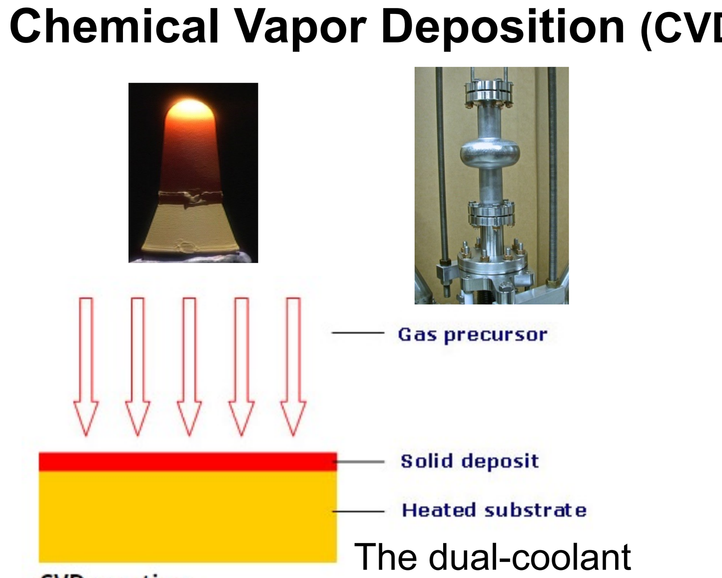
- **This study focuses on the identification of defects in compounds for extreme applications: Nb_3Sn used in superconducting radio frequency cavities and SiC for fusion reactors.**
- **Machine learning algorithms have been applied to process atomistic structure images of interfaces of Cu/Nb_3Sn and defect evolution with an increase in irradiation dose in SiC.**
- Advanced technology has facilitated the emergence of cutting-edge medical technologies, such as compact superconducting cyclotrons for external beam therapy with protons and ions.
- Thermo Fisher Scientific Talos F200X FEG-STEM and JEOL ARM200CF S/TEM were used for analytical microscopy for chemical composition using scanning transmission electron microscopy-energy dispersive X-ray spectroscopy (STEM-EDS) [1,2]. The process culminated with taking images of SiC defects that were analyzed through unsupervised machine learning algorithms.
- The results from the analysis provide insights into defect behavior to create strategies for maximizing the life and strength of materials[1,3]. The broader impact of this work would also result in cost and size reduction advantages in isotope production.
- **We found defects with better resolution and confidence in the microstructure of these materials for extreme conditions.**

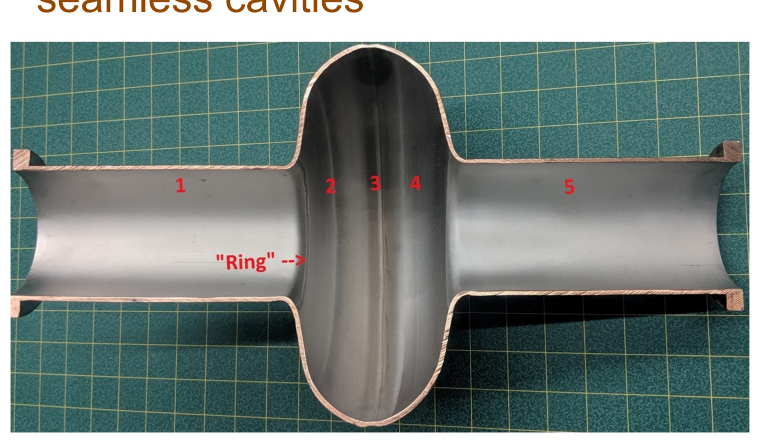
Background on materials and processing

Thin-film CVD Nb_3Sn-on-Cu via pre-alloyed precursors

Bailey Tool seamless cavities

Chemical Vapor Deposition (CVD)



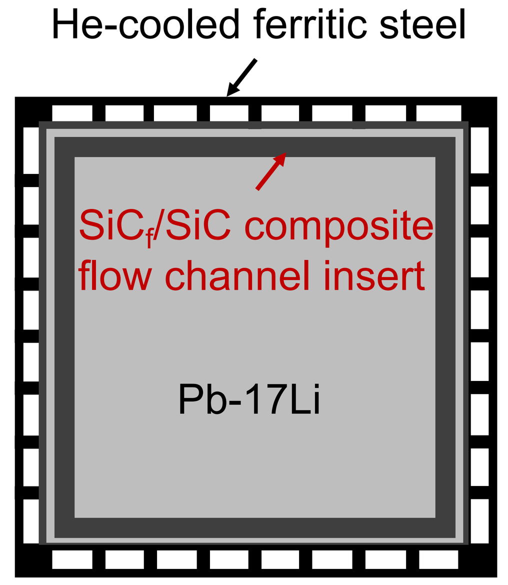


Ultramet CVD Nb_3Sn on bare Niowave welded copper cavity (SN43-45) using FSU A-Nb:Sn-1 precursor

The dual-coolant helium/lead-lithium (DCLL) blanket is a candidate for a fusion DEMO reactor.

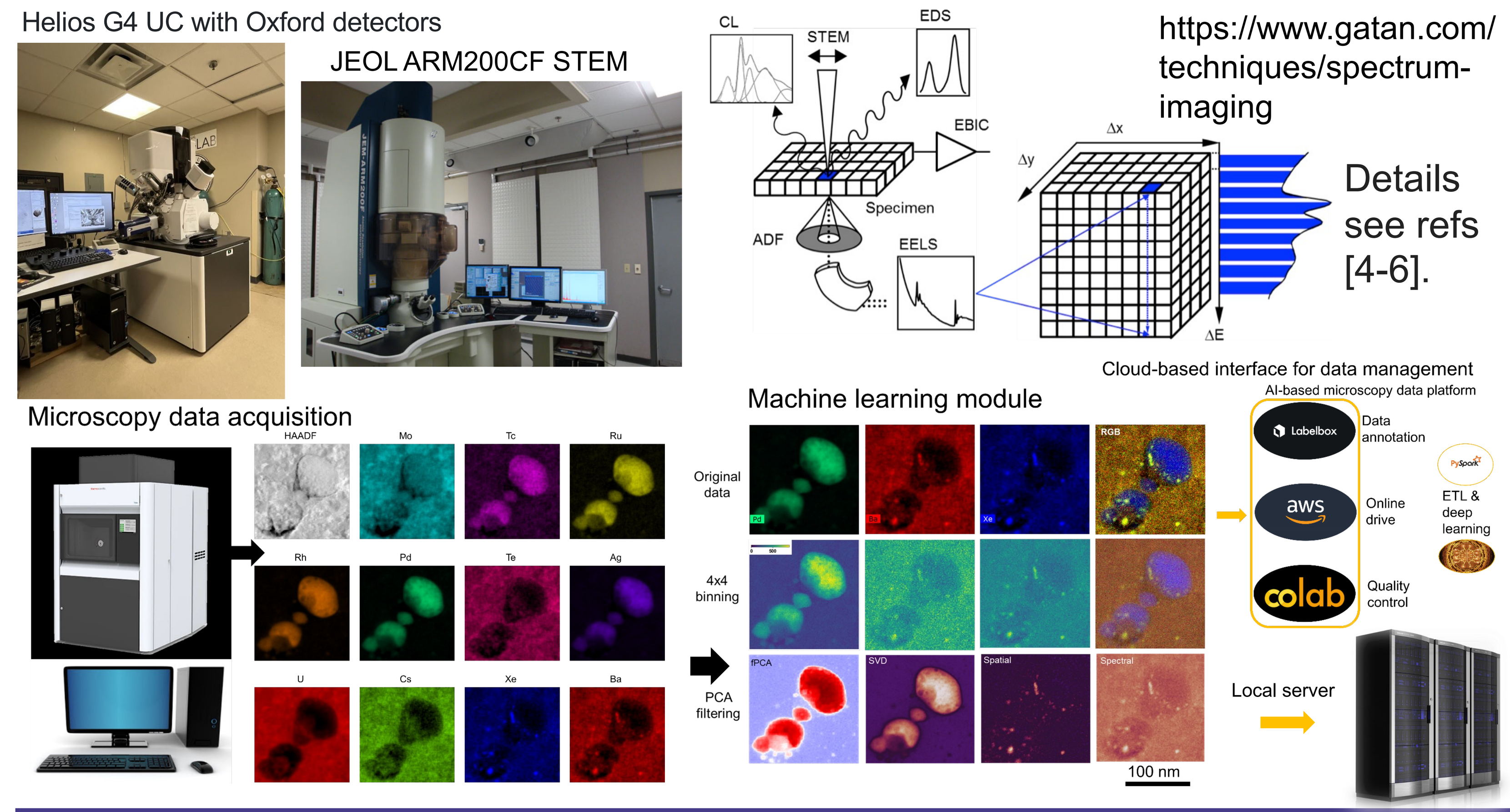
DCLL uses SiC as the flow channel insert (FCI) in the coolant ducts to provide electrical and thermal insulation.

SiC for fusion



Cross section of the Pb-Li breeder unit cell of DCLL blanket [7].

Methods on characterization and data processing

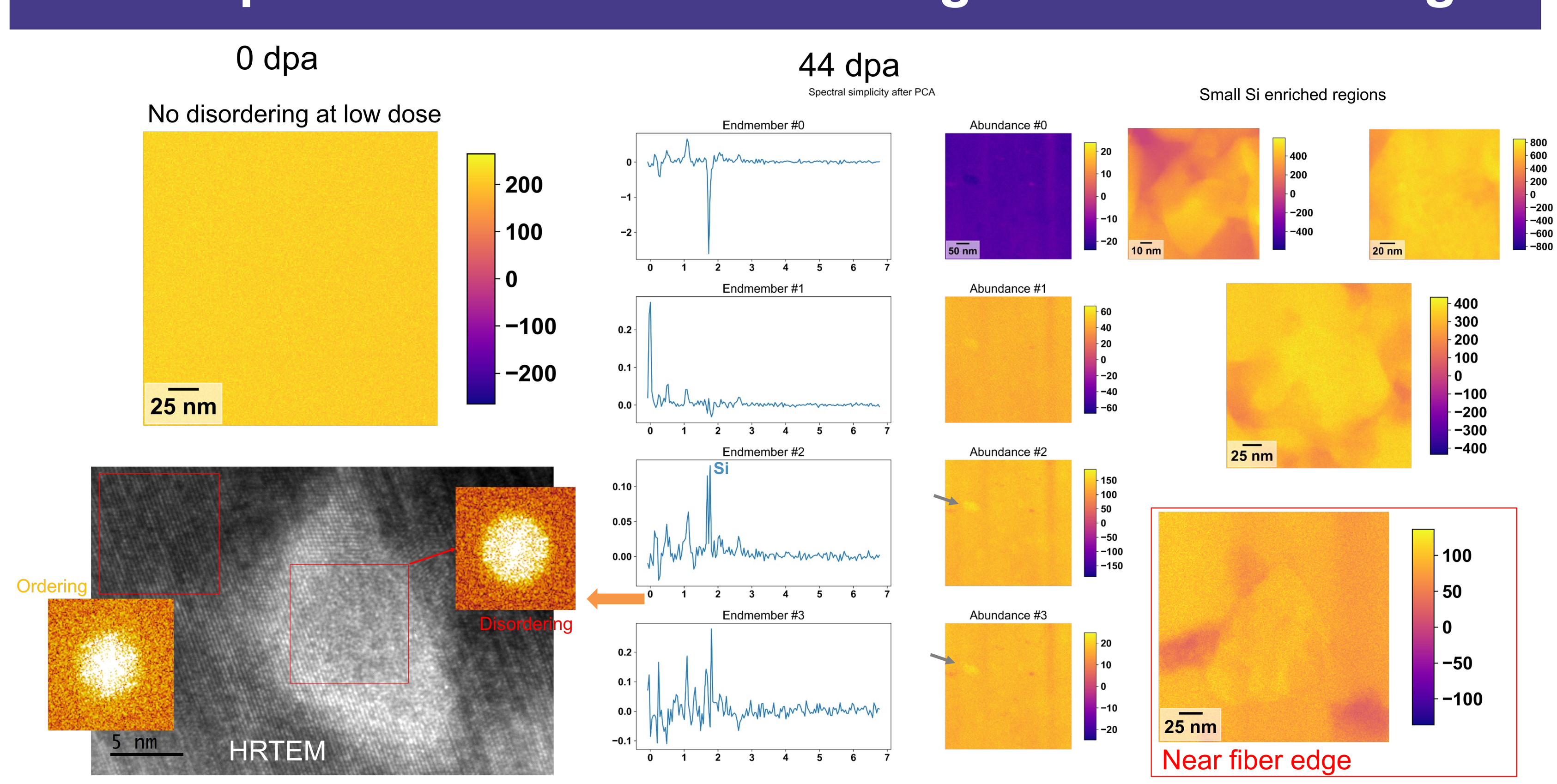


General application and coding

- SiC is a wide gap semiconductor with decent radiation tolerance leads it to serve in extreme environments (space exploration, fusion reactors).
- The microstructural evolution of SiC under these conditions needs to be examined with modern electron microscopy.
- Establishing a machine learning (ML) platform using existing Python-based data science/ML libraries and data visualization tools to exhibit the defect evolution of SiC composite fiber with the increase of irradiation dose.
- An ML-enhanced approach helps better understand the defect behavior and proposes mitigation strategies to reduce their negative implications on structural materials.

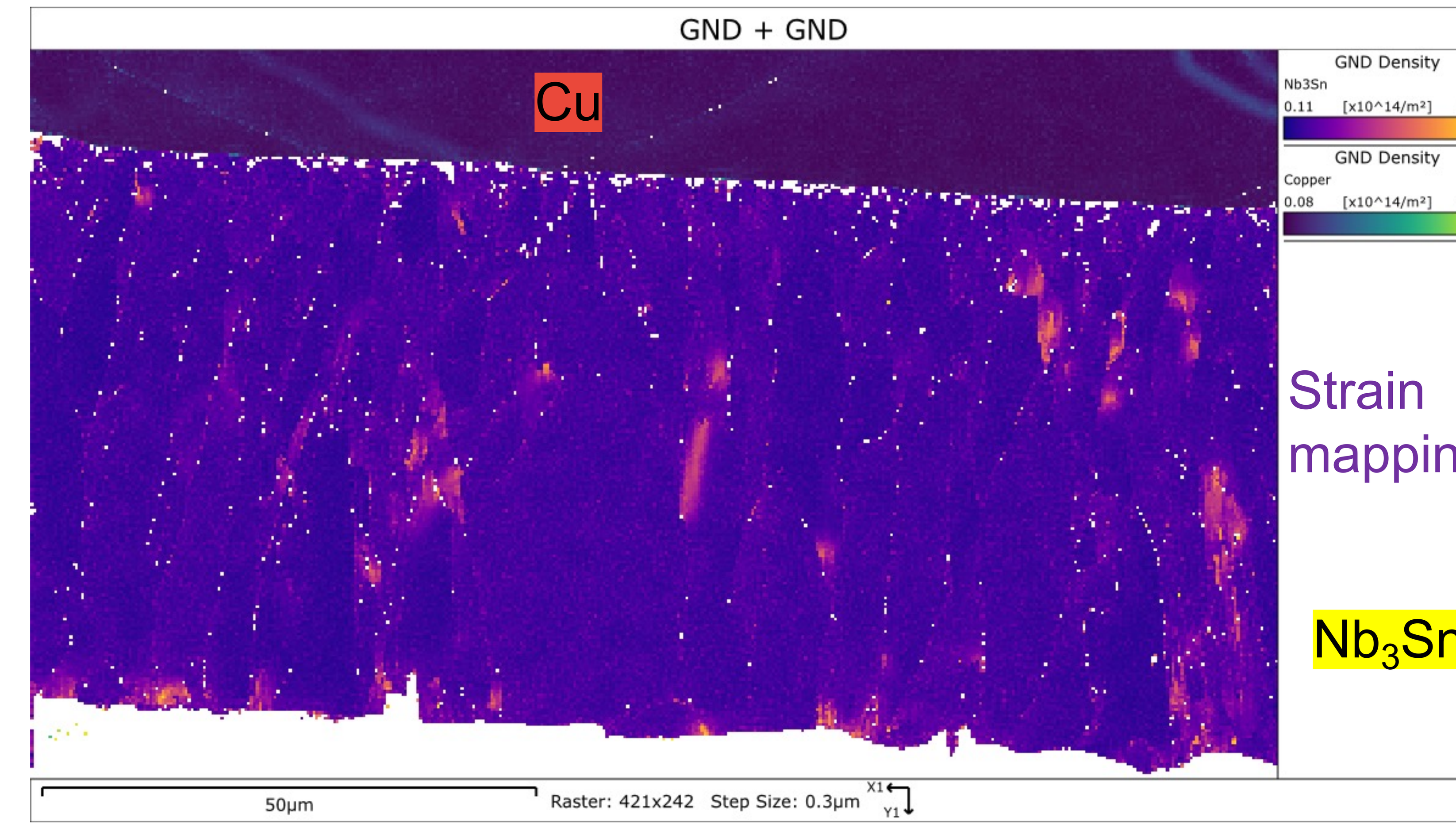
SCAN ME

Si Map in the irradiated SiC using Machine Learning

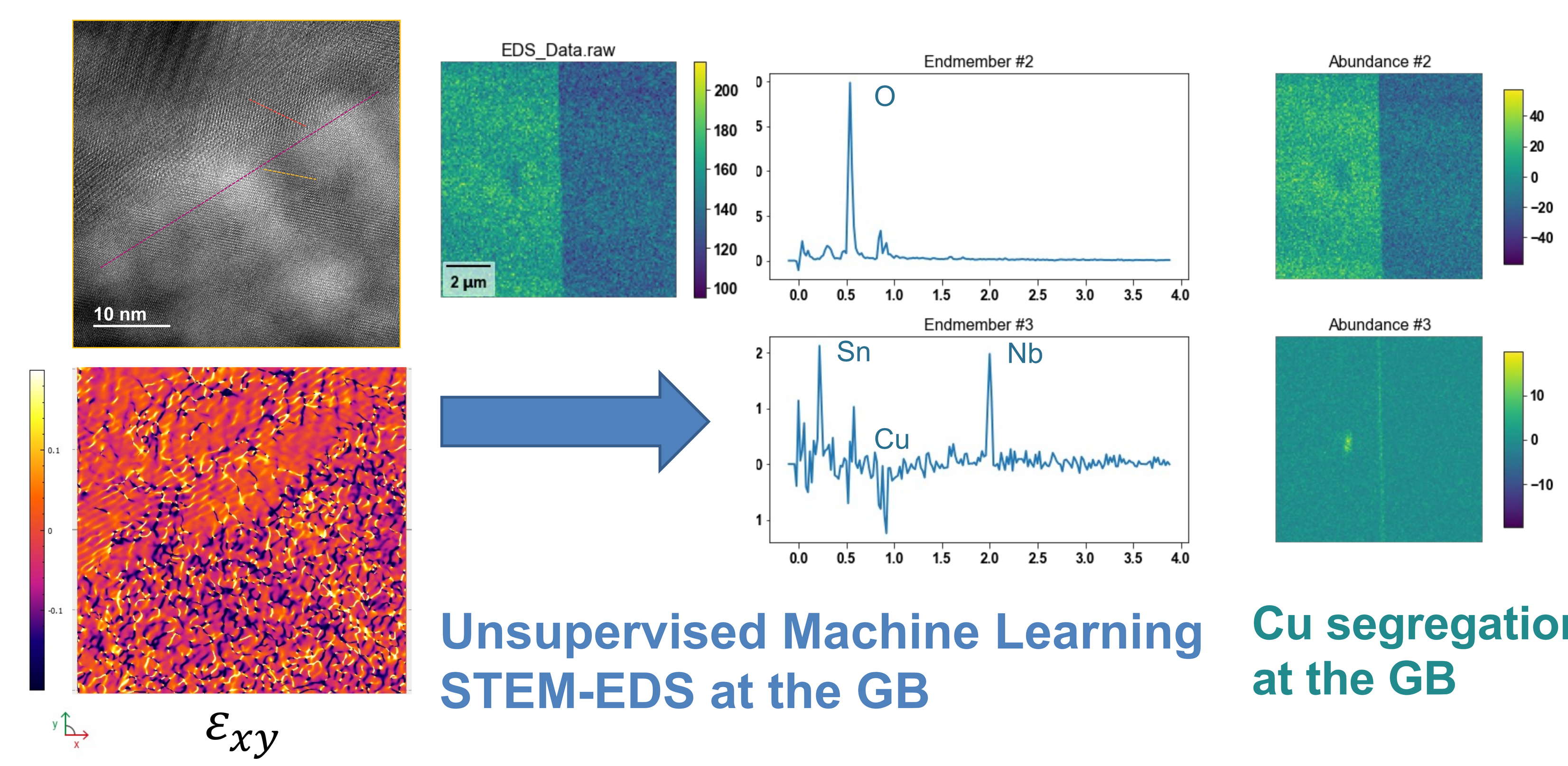


STEM-EDS maps on Si inside random single grains denoised the artifacts and low-counting background signals.

Thin-film Nb_3Sn-on-Cu ILC cavities interface



Looking at the Nb_3Sn Grain Boundary



Unsupervised Machine Learning STEM-EDS at the GB

Cu segregation at the GB

Summary

- The defect evolution was experimentally investigated through the construction of atomistic-level microscopy characterization enhanced by machine learning.
- We found a detailed analysis of cavities and elemental distribution that is helpful to understand the effects of radiation of SiC and heterogeneity in Nb_3Sn thin films.

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CONTACT INFORMATION: nsb21b@fsu.edu

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