

Sarah Scott
srs108@duke.edu

ETI Annual Workshop February 20 – 21, 2024

Introduction

- Microscopic pores in 3D printed metallic structures, crucial for nuclear reactor development, can be detected pre-deployment via destructive and nondestructive methods.
- Scanning electron microscopy (SEM) efficiently images large sections with low spatial resolution (10 nm/pixel).
- Thermal Tomography (TT), employing Pulsed Infrared Thermography (PIT) data, reconstructs thermal effusivity, aiding defect visualization.
- Multitask learning facilitates training a single model for multiple tasks, providing multiple predictions, parameters, and/or segmentation masks.
- Shared network parameters enhance performance across multiple tasks compared to individual task-focused models.

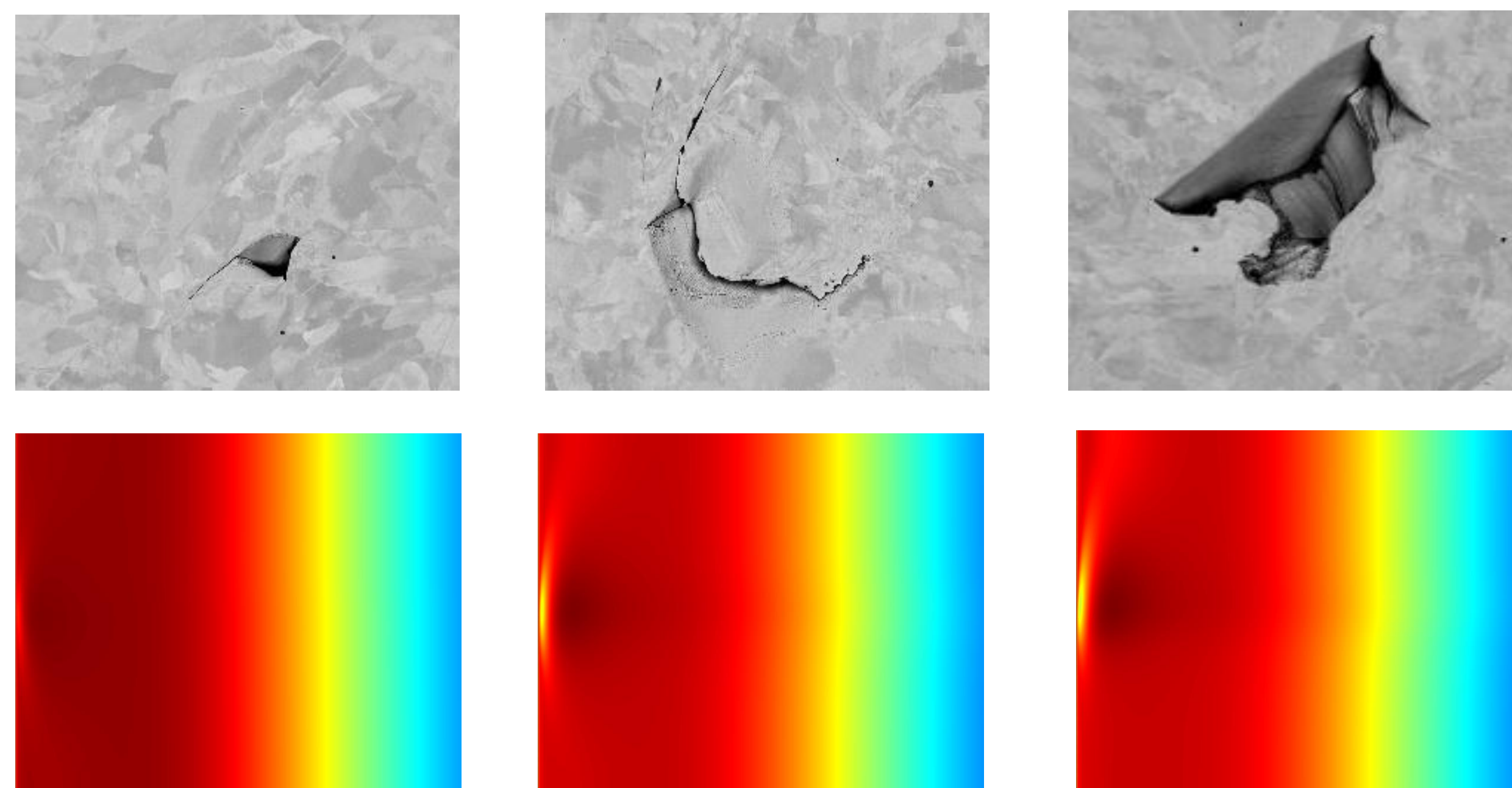


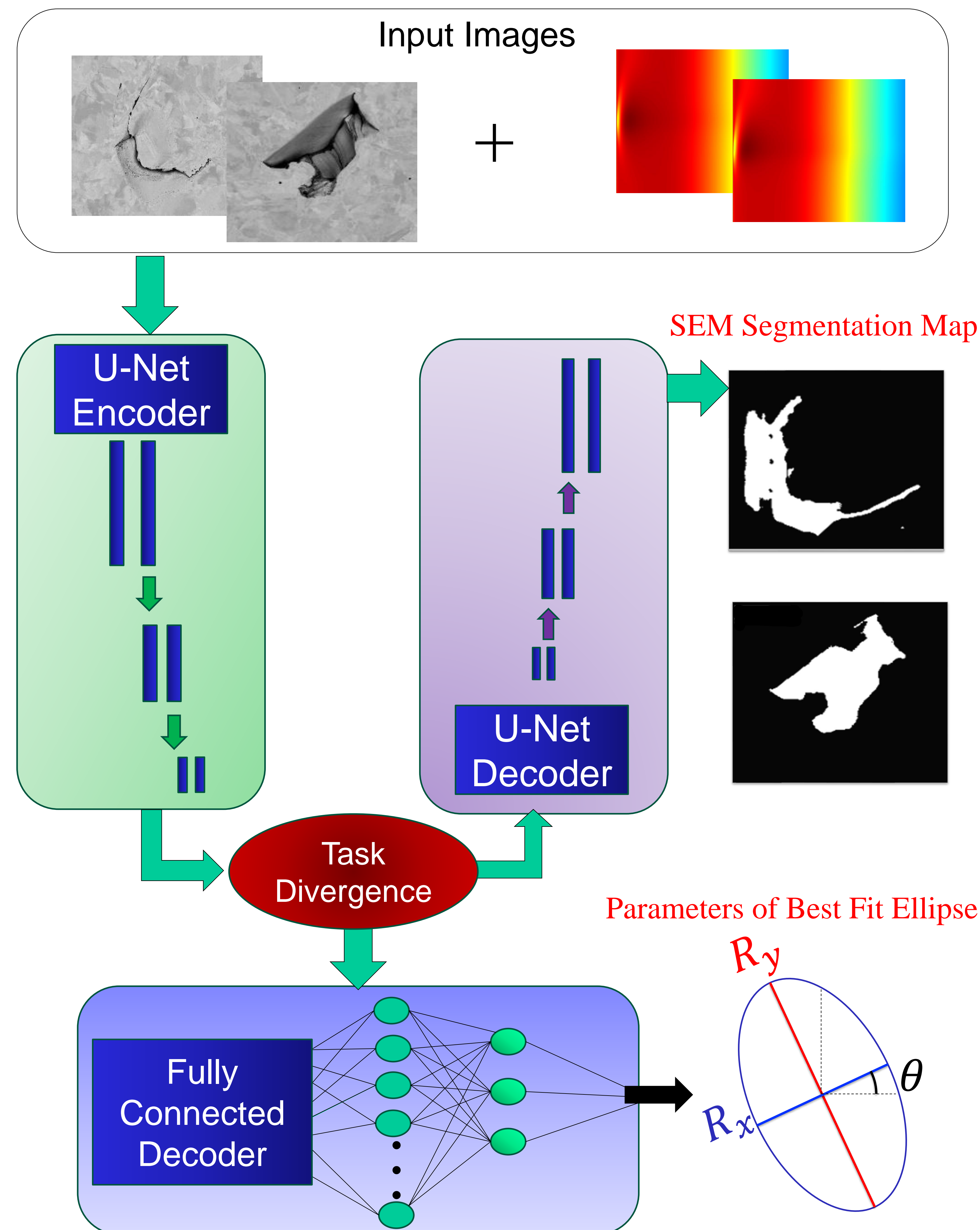
Figure 1: Sample SEM images (top) and sample simulated Thermal Tomography images (bottom)

Goals & Objectives

- We propose a multi-task learning network featuring a shared U-Net encoder for both classification and segmentation tasks.
- Enhance parameter prediction for best fit ellipse extraction from TT images and improve segmentation accuracy in SEM images.
- We aim to exploit similarities between images of defects of additively manufactured metals despite the disjoint nature of the datasets,

Methods

- Novel multitask learning approach, simultaneously performing classification of synthetic TT images, and segmentation of experimental SEM images.
- MTL network is implemented as a shared U-net encoder between the classification and the segmentation tasks which then splits into separate branches for each task, generating a binary segmentation mask for the SEM images, and predicting characteristic parameters for the elliptical defects in simulated TT images.



Results

- Improved segmentation maps assessed via Binary Cross Entropy and Intersection-Over-Union as compared to single task performance (minimize BCE, Maximize IoU).
- Improvement in parameters of best fit ellipse including angle of orientation, semi major, and semi minor radii.

Data Set	Metric	Single-Task	Multi-Task
Training	BCE	0.03	0.01
Testing	BCE	0.31	0.03
Training	IoU	0.88	0.92
Testing	IoU	0.81	0.87

Table 1: Binary Cross Entropy (BCE) loss and mean Intersection-over-Union (IoU) for a Single-Task U-Net model, and Multi-Task Learning network that includes U-Net model.

Variable	θ		R_x		R_y	
	Single-Task	Multi-Task	Single-Task	Multi-Task	Single-Task	Multi-Task
Pearson R	-0.34	0.82	0.89	0.96	0.92	0.97
Spearman R	-0.28	0.80	0.92	0.96	0.93	0.96

Table 2: Values of Pearson r and Spearman ρ correlation coefficients for predictions of elliptical defect angle of rotation θ , semi-major axis R_x , and semi-minor axis R_y .

Future Directions

- Augment non-destructive TT data with experimentally captured pulsed infrared thermography images.
- Employ semi-supervised training, using predictions in segmentation and classification tasks as ground truth labels, an approach suitable for smaller datasets.
- Extend multi-task learning analysis to diverse image defect datasets, such as high-resolution X-Ray computed thermography, as well as lower resolution ultrasonic or eddy current images.