Deep learning model for prediction of laser-induced damage growth on NIF optics

Robin E. Yancey, Christopher F. Miller, Jae Hyuck Yoo, Yoonsoo Rho, Christopher W. Carr, Ted A. Laurence
Lawrence Livermore National Laboratory 7000 East Ave., Livermore, CA 94550, USA

INTRODUCTION

Recycling of the National Ignition Facility (NIF) fused silica final optics allows regular laser operation above the exit surface damage growth threshold. While large damage sites tend to grow exponentially upon additional laser exposures – requiring repair when an optic is recycled – smaller sites grows in a stochastic manner, making the necessity of repairing an individual site ambiguous.

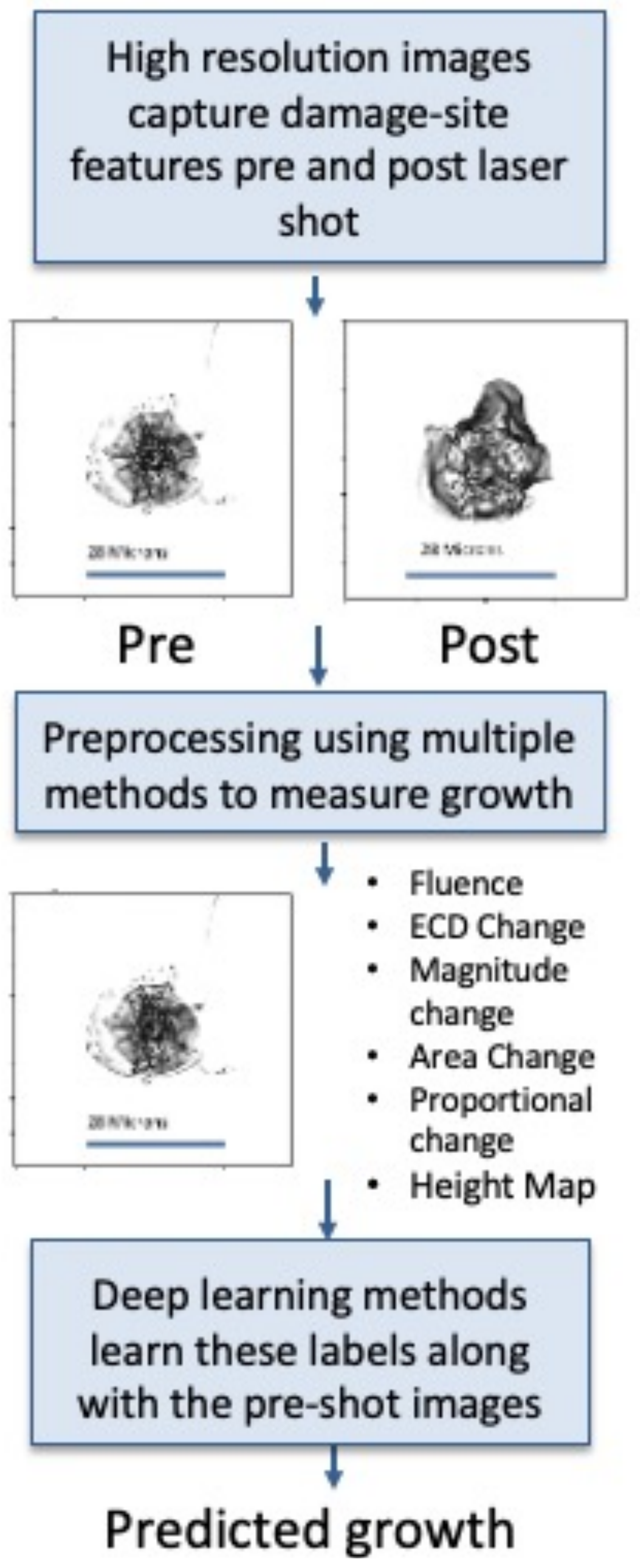


Fig. 1. Workflow of the proposed model from input images to label prediction

Therefore, the development of a model that can accurately predict the susceptibility of damage site growth is necessary to reduce the number of repairs. In this work, computer vision techniques have been used to extract high level details from Laser Confocal Images (LCI) to predict the levels of damage growth. The developed model first employs a pre-processing framework to label each associated pre-shot input image in a variety of different methods and prepare input pre-shot images. In the second phase, a deep learning framework is trained on this data to learn this information.

METHODS

Pre-processing: One method of growth measurement involves aligning corresponding pre and post images with Fourier Mellin[1] Method. Then, subtracting them from each-other element-wise allows capturing of both positive and negative change information as a "Difference Image".

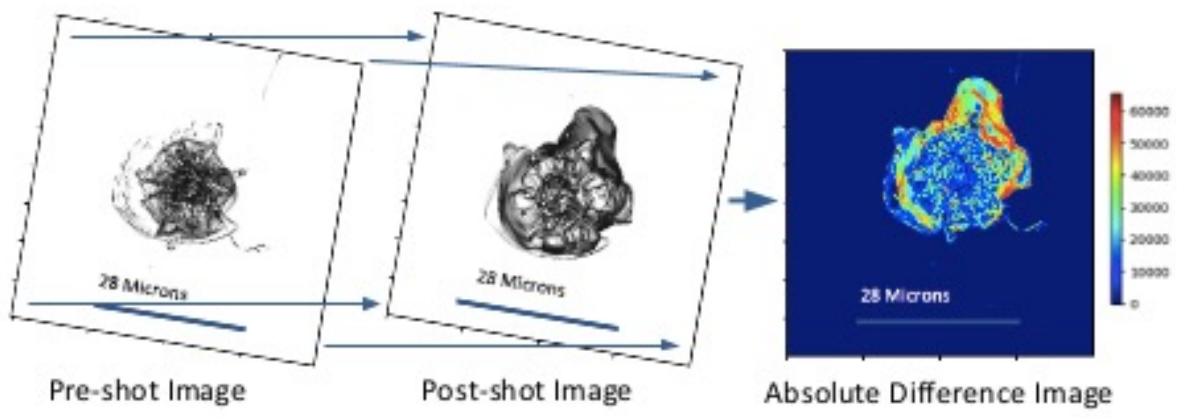


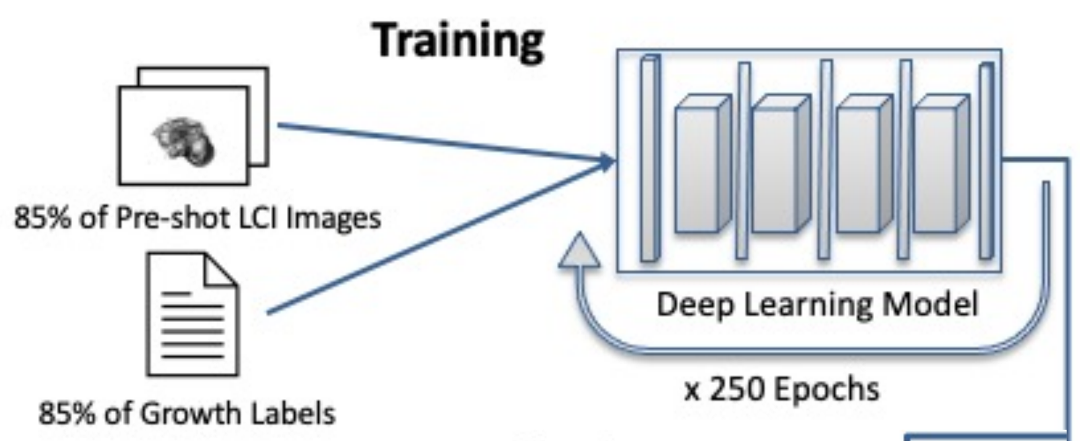
Fig. 2. Difference Image Generation

The summation of the absolute value of all pixel intensities in the Difference Image is used to precisely quantify growth behavior associated with each pre-laser-shot image

$$\text{Growth Magnitude Label } (Y_{True}) = \frac{1}{\max(|I_{post}-I_{pre}|)}\int |I_{post}-I_{pre}|\, dA_{I>Imin}$$

Eq. 1. Difference Image Growth Calculation

Deep learning: The input data is divided up into train, and test sets. Then, a hybrid transformer-based state-of-the-art deep learning model is trained for ~300 epochs, before the best evaluated model is serialized for testing on new data.



The trained model is evaluated on a subset of the pre-processed images to estimate how well it performs on unseen data.

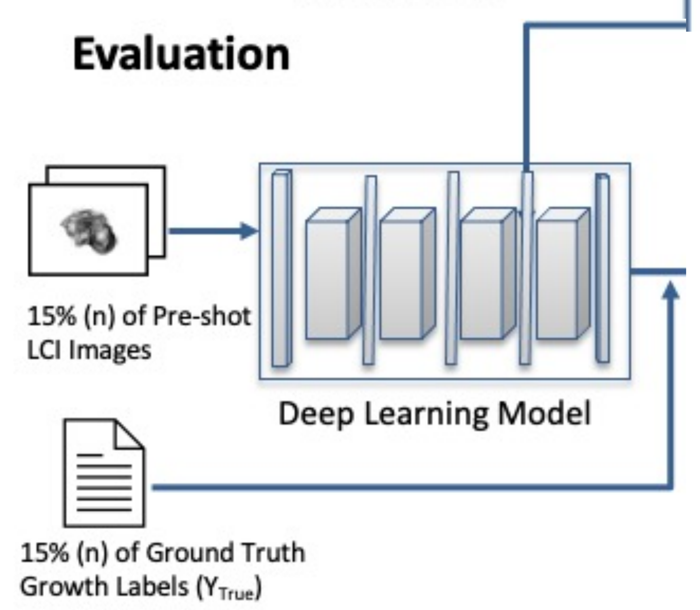


Fig. 3. Deep Learning Model Training and Evaluation

RESULTS

Several methods of growth measurement and corresponding accuracy metrics were used to assess the model. Two will be discussed here:

- **Binary Accuracy** is the percentage of damage sites correctly predicted as above or below a specific area growth threshold (the dataset mean area growth - 83 microns).
  - Here the area of the site is calculated similarly to the Pre-processing Methods section to the left.
- **Average MAE of ECD Growth Order** helps compare our method to the current method used in production.
  - The current method, simply chooses the next site to mitigate based on the next highest pre-shot Equivalent Circular Diameter (ECD)[2] (assuming this site is most likely to have the highest ECD growth).
  - Therefore, we can compare each set of predictions sorted according to predicted ECD growth to those sorted by true ECD growth to get an MAE.
  - Since this MAE depends on the size of the test dataset, it is then divided by the length of the dataset to get a percentage of a given dataset.

	MAE of ECD Growth Order (percent of dataset)	Binary Accuracy
Our Method	30%	88%
Current Method	34%	NA

Table 1. Model Error and Usability Assessments

Conclusion

Using all 10 comparison metrics, the model described here shows usefulness and performs better than the current method.

REFERENCES

1. Crowdy, D. Fourier–Mellin Transforms for Circular Domains. *Comput. Methods Funct. Theory* **15**, 655–687 (2015).
2. C. Wren Carr, David A. Cross, Zhi M. Liao, Mary A. Norton, Raluca A. Negres, "The stochastic nature of growth of laser-induced damage," Proc. SPIE 9532, Pacific Rim Laser Damage 2015: Optical Materials for High-Power Lasers, 953212 (22 July 2015)