Predicting Stress-Strain Curves from Indentation Curves using Deep Learning

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Objectives

- Build an LSTM-based model to predict Stress-strain data from indentation data
- Analyze the effect of additional features on the performance of the model

Introduction

- Obtaining stress-strain data is more cumbersome than micro-indentation data due sophistication of procedure involved.
- Stress-strain analysis necessitates specialized equipment, precise load-applying mechanical testing machines, meticulous sample preparation, alignment to ensure consistent and reliable results.

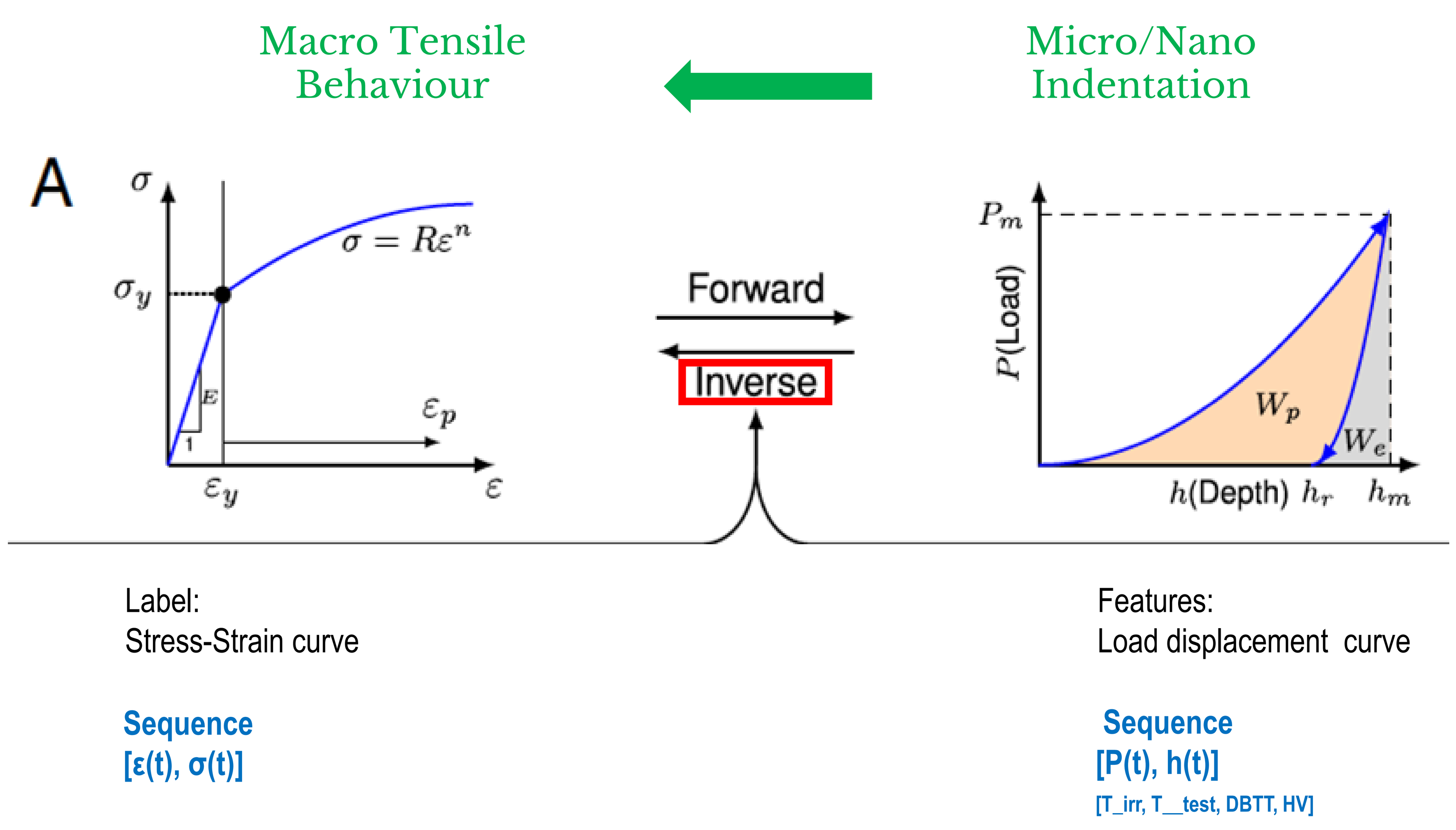


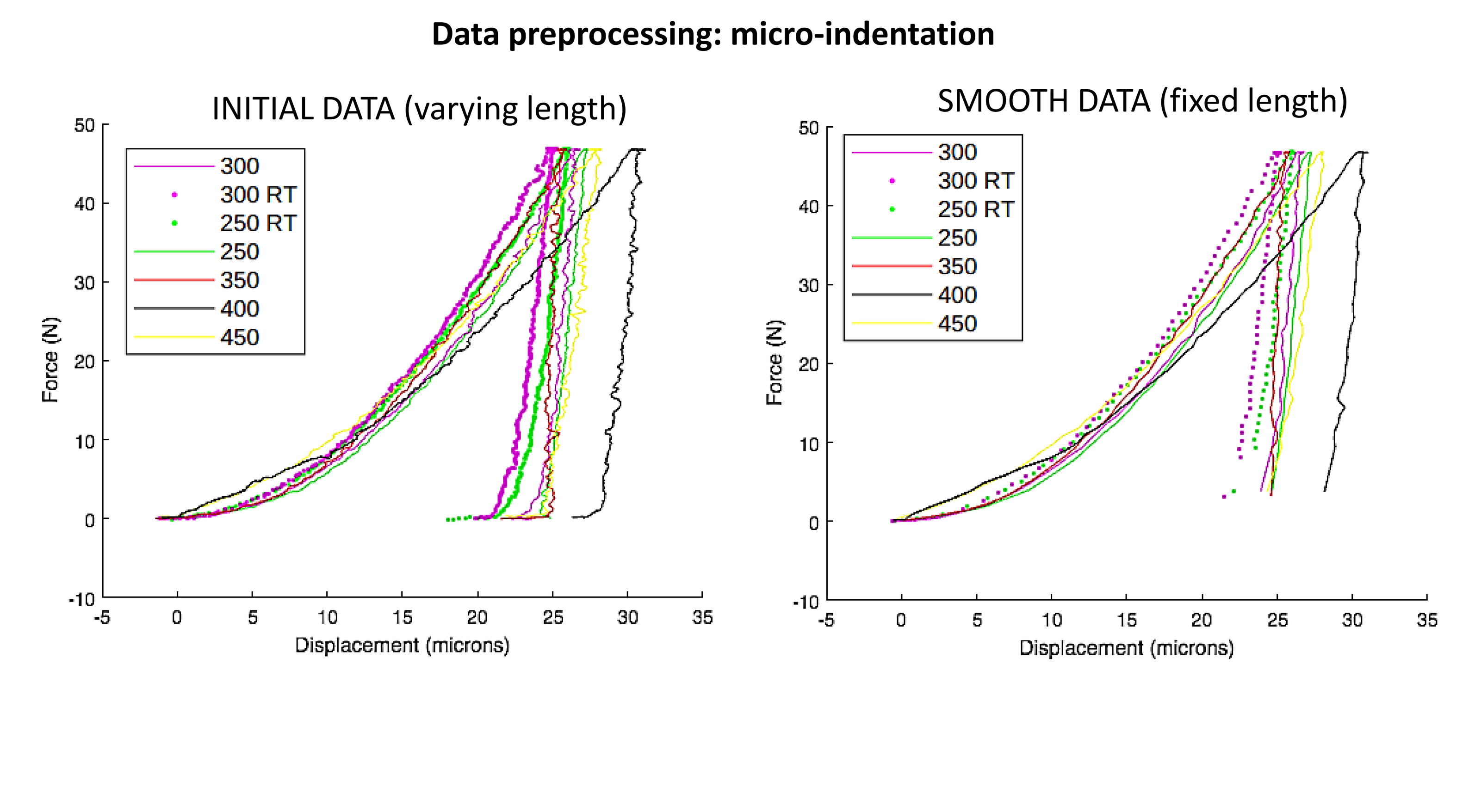
Figure 1. Micro to Macro: Inverse prediction.

Thus, we want to use Micro/Nano-indentation data to predict stress strain curves. In pursuit of this we try working with an LSTM based model

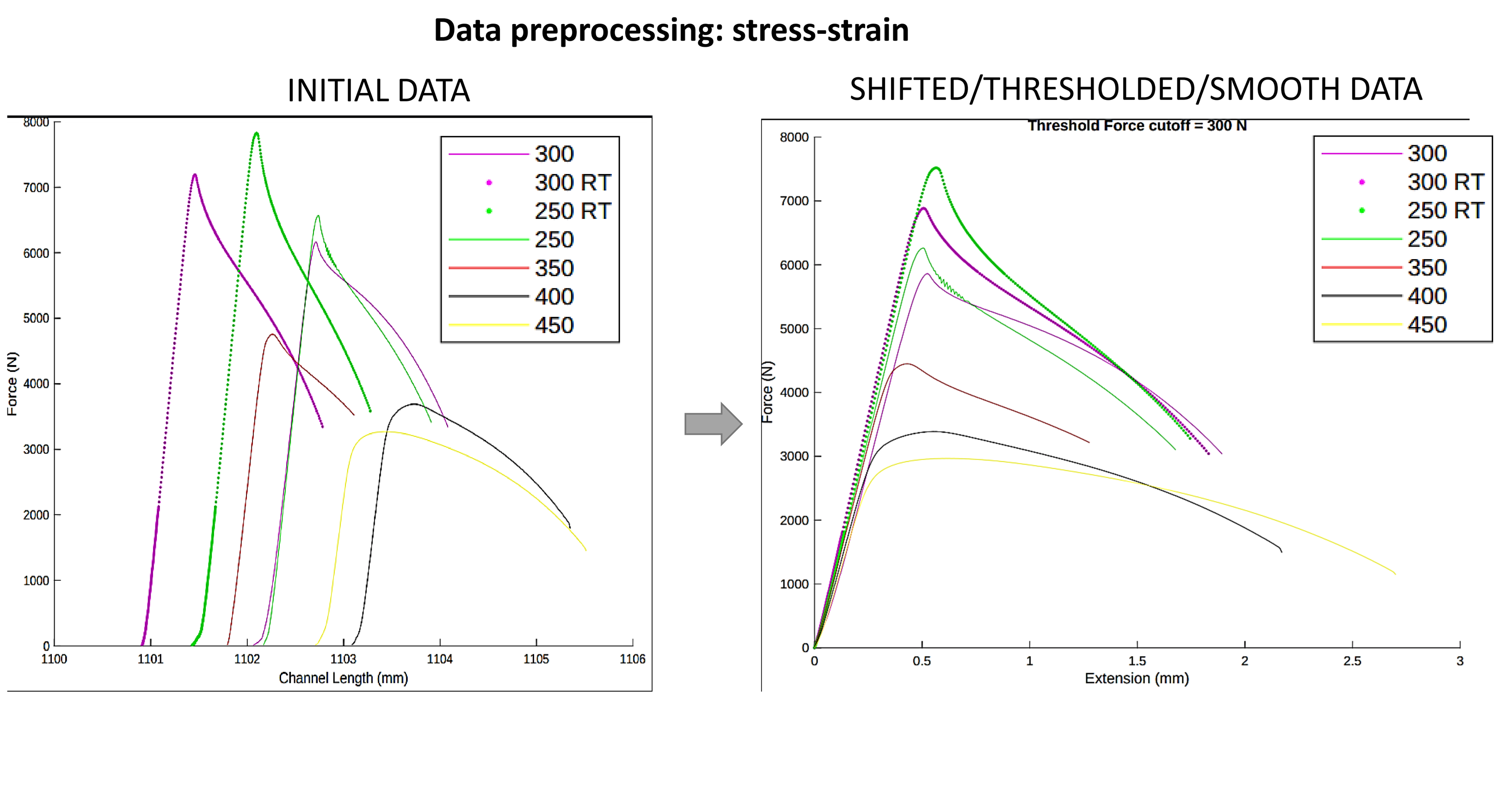
Data Pre-processing

Using the experiments we performed on Irradiated Eurofer 97, we generate the dataset for various temperatures.
To make the data easier to work with, and to better generalize, the following pre-processing steps were applied

- **Smoothing:** Reduce noise and irregularities
- **Uniform Sampling:** Ensure a consistent length across all samples
- **Shifted:** Calibrated to origin



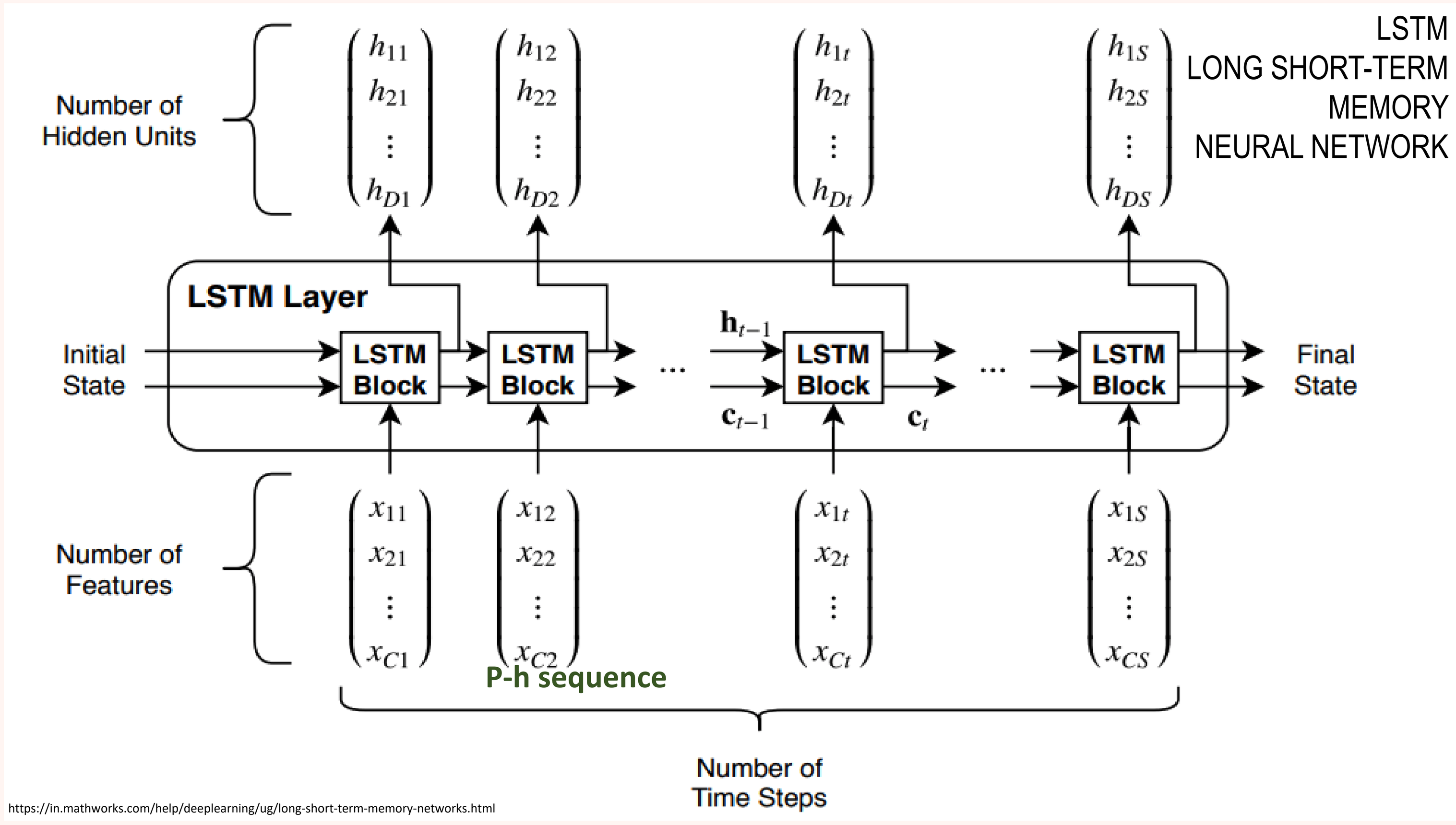
(a)



(b)

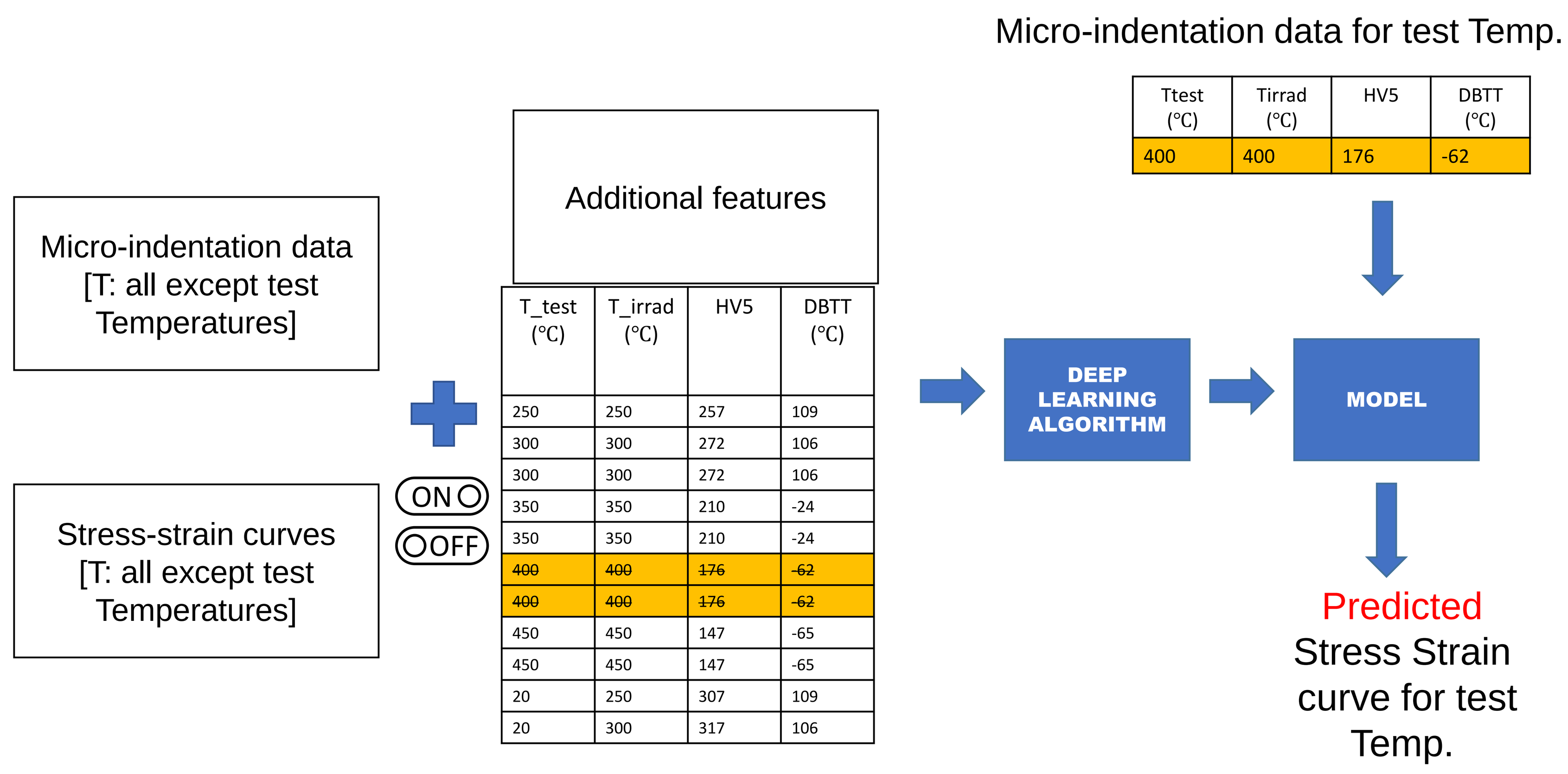
Why LSTM?

- LSTM, a recurrent neural network architecture that captures long-term dependencies in sequential data
- Memory cells and gating mechanisms to selectively retain and forget information over time, model learns and remembers patterns across sequence



Workflow

To check the effect of features, additional features can be added or not.
The data for one temperature is held off as test



Ttest (°C)	Tirrad (°C)	HV5	DBTT (°C)
400	400	176	-62

T_test (°C)	T_irrad (°C)	HV5	DBTT (°C)
250	250	257	109
300	300	272	106
300	300	272	106
350	350	210	-24
350	350	210	-24
~~400~~	~~400~~	~~176~~	~~-62~~
~~400~~	~~400~~	~~176~~	~~-62~~
450	450	147	-65
450	450	147	-65
20	250	307	109
20	300	317	106

Figure 3. Workflow of Data and Model

Results

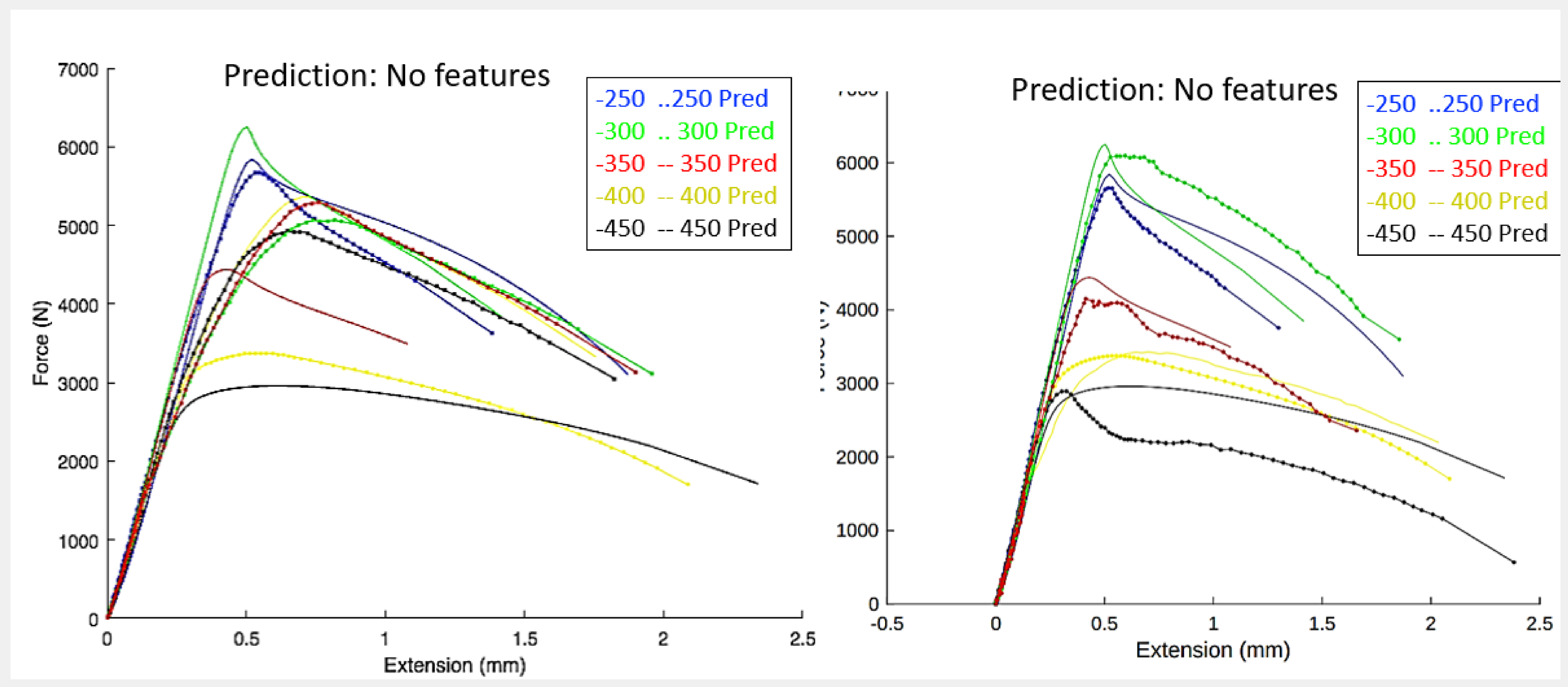


Figure 4. Results: Features v/s No Features

Summary

- LSTMs powerful enough to learn good mappings from P-h curves to Stress Strain (SS) curves using very few data points.
- Extra Features are critical for learning good mappings
- General rule of thumb: More relevant data => Better learning

Further Work

Nano-Indentations (P-h for various temperatures), More features, Spherical indentations, Electrical resistivity, non irradiated Tensile data, other materials

References

[1] Lu Lu, Ming Dao, Punit Kumar, Upadrasta Ramamurty, George Em Karniadakis, and Subra Suresh. Extraction of mechanical properties of materials through deep learning from instrumented indentation. *Proceedings of the National Academy of Sciences*, 117(13):7052–7062, 2020.