Data-Driven Prediction of Tensile Strength in Material Extrusion Additive Manufacturing

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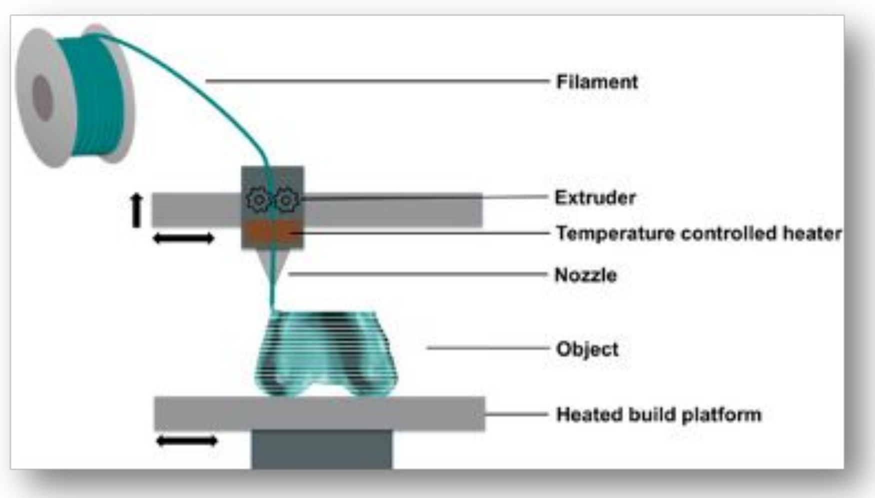
Overview

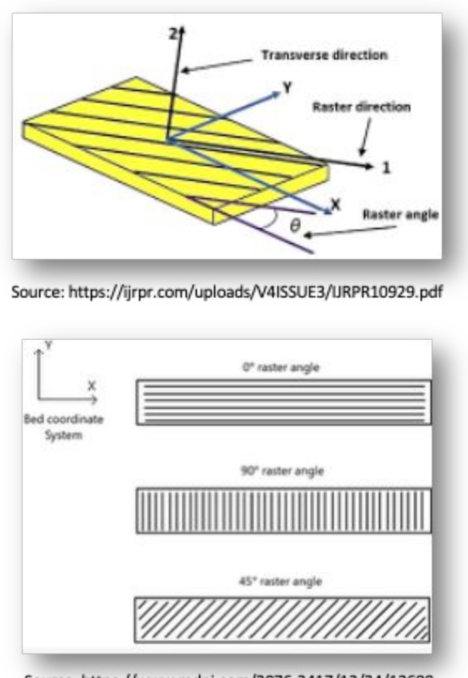
Introduction

As material testing can be time consuming and costly, this study explores the use of machine learning models as predictive method for evaluating tensile properties. By training regression models on limited experimental data, the research aims to accurately predict the mechanical properties of additively manufactured parts made from Technomelt PA 6910.



Source: https://www.mdpi.com/1420-3049/25/24/5929

Figure-1: Fused Deposition Modeling 3D printing process



Source: https://ijrpr.com/uploads/V4ISSUE3/IJRPR10929.pdf

Source: https://www.mdpi.com/2076-3417/12/24/12690

Figure-2: Raster pattern orientations in printed parts.

Methodology

- The training set consisted of 124 sample, containing the following data along with some metadata.
  - Input: Text (°C) - extruder temperature, h (mm) - layer height, and Raster angle (°)
  - Output: Young's Modulus (MPa), initial stress (mm/mm), strain (MPa) and final stress (mm/mm) and strain (MPa).
- Machine learning models Linear Regression (LR), Polynomial Ridge Regression (RR), K-Nearest Neighbors (KNN), and Gaussian process regression (GPR) were implemented using the scikit-learn library in Python and applied to the test data set of 30 samples and predictive accuracy is assessed.
- The model performance was evaluated using root mean squared error (RMSE) and mean absolute error (MAE).

Source: https://www.sciencedirect.com/science/article/pii/S1369702118303663

Figure-3: A layered Structure of a 3D component.

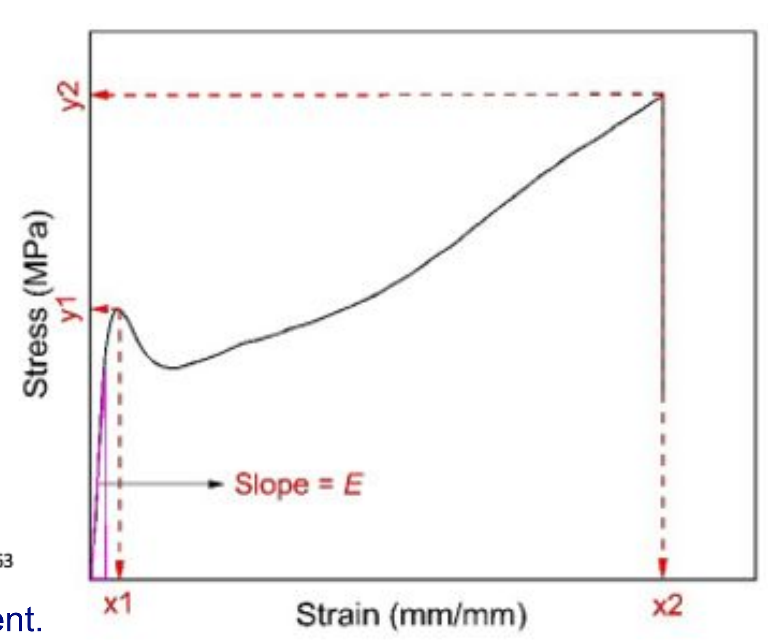


Figure-4: Typical stress-strain curve

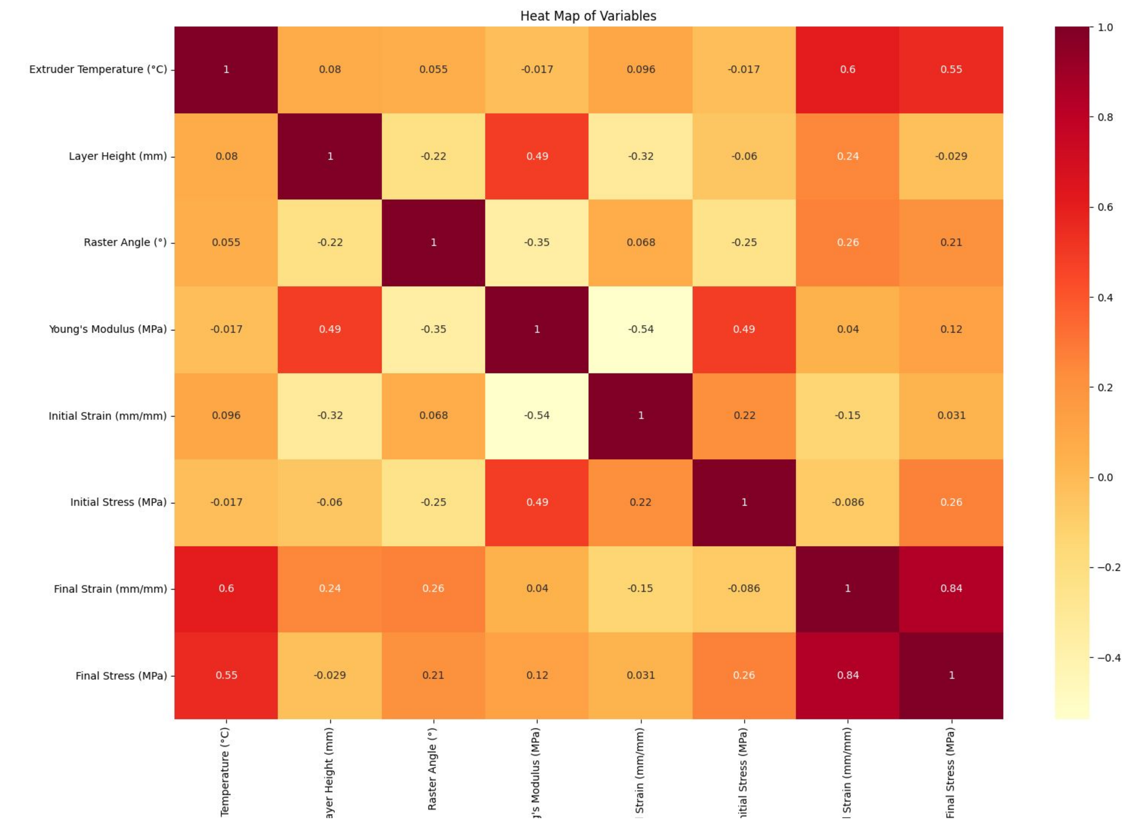


Figure-5: Heatmap showing correlations between input parameters and mechanical responses.

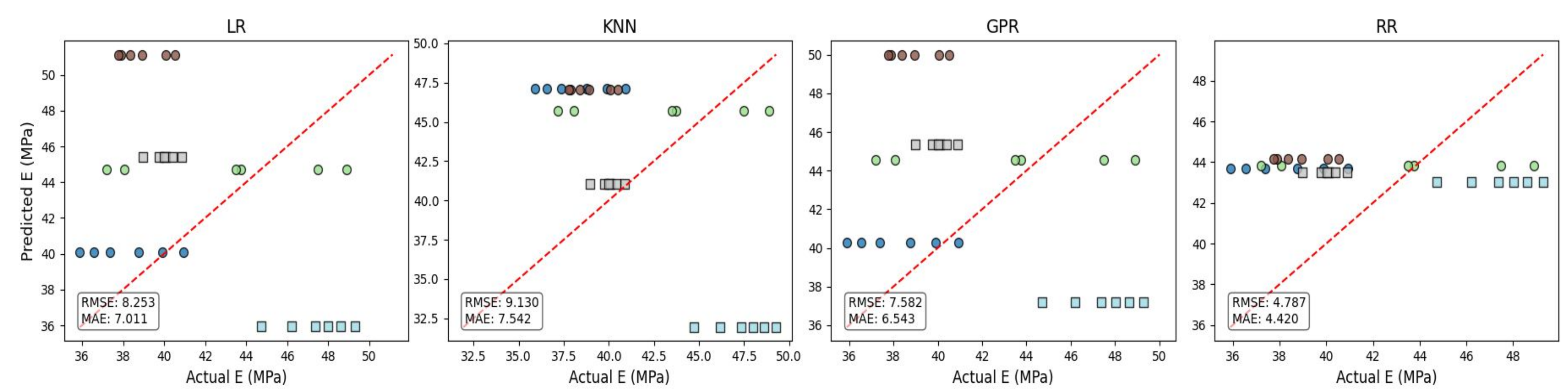


Figure-6: Predicted vs Actual for E (MPa)

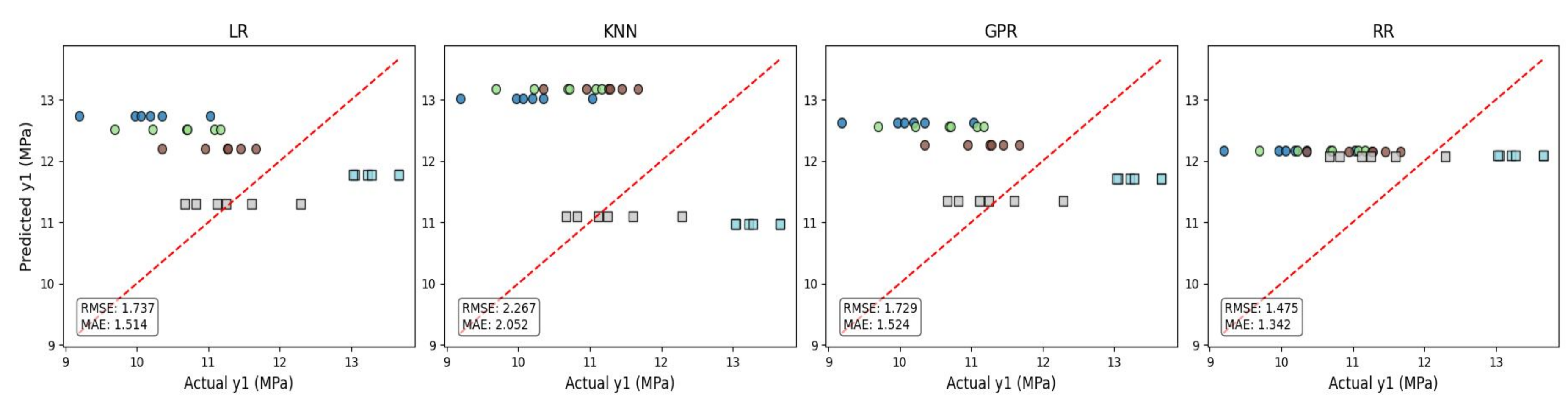


Figure-7: Predicted vs Actual for y1 (MPa)

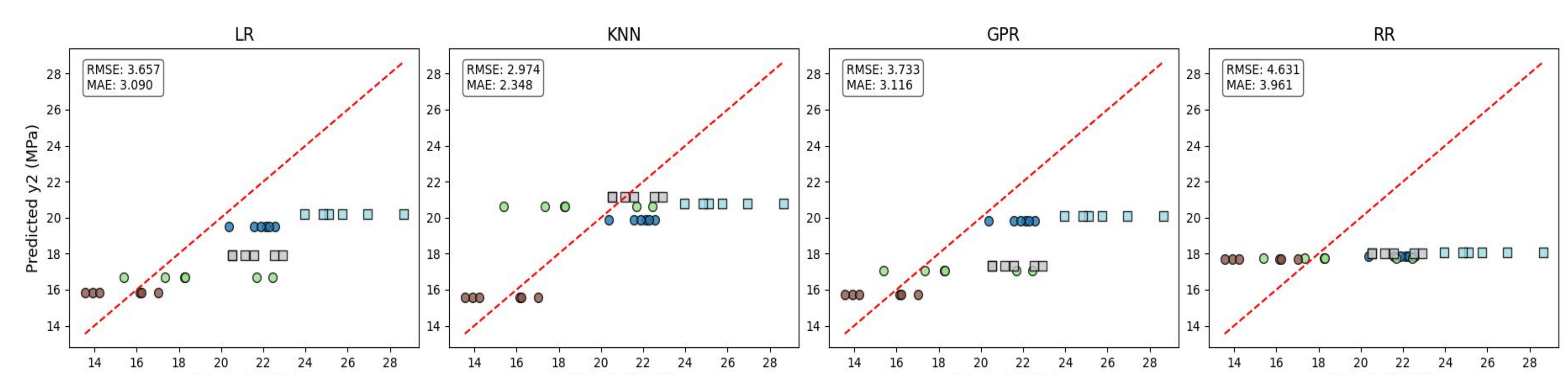


Figure-8: Predicted vs Actual for y2 (MPa)

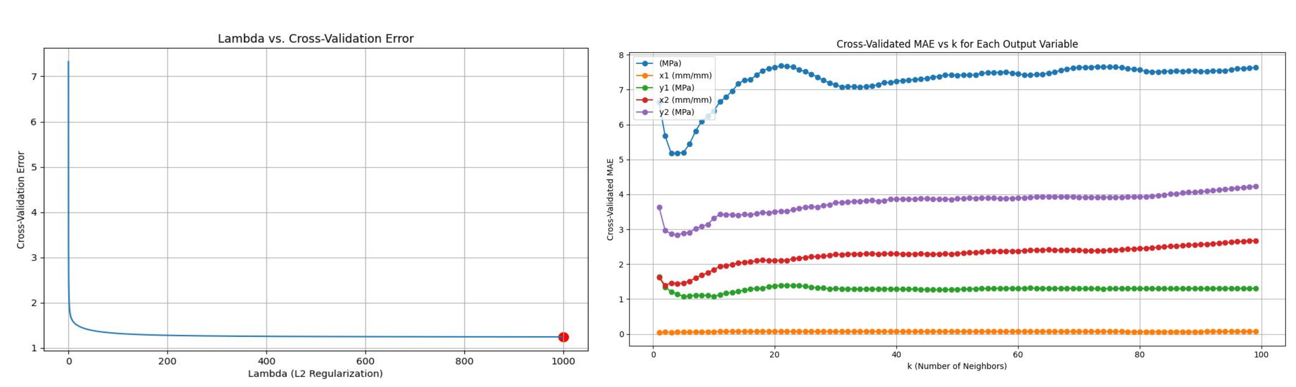


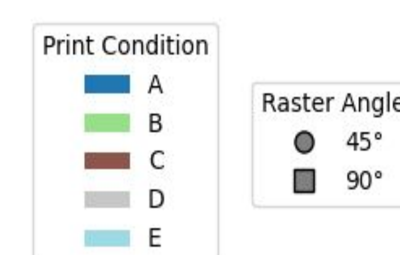
Figure-9: Hyperparameter tuning completed for Ridge Regression (λ) and KNN (k-value).

Results

Output Parameter	*Best Model*	*MAE*	*RMSE*
Young's Modulus (E)	Ridge Reg.	4.420	4.787
Initial Strain (x1)	None	32.366	32.403
Initial Stress (y1)	Ridge Reg	1.342	1.475
Final Strain (x2)	None	938.582	948.612
Final Stress (y2)	KNN	2.348	2.974

Table-1: Model Evaluation

- RR consistently shows predictions closest to the ideal line for E and y_1, with the lowest RMSE/MAE values.
- KNN performs best for y_2, suggesting it captures localized variations well.
- GPR underpredicts high values and shows the widest spread, especially for E.
- All models had difficulty capturing x_1 and x_2 accurately, with predictions tending to underestimate the true values.



Print condition	T (°C)	h (mm)	θ (°)
A	231	0.06	45
B	217	0.18	45
C	214	0.36	45
D	216	0.34	90
E	226	0.08	90

Table-2: Print parameter conditions for testing data

Conclusion

- **Ridge Regression:** Most reliable overall; lowest errors for Young's modulus (E) and yield stress (y_1); stable across all outputs.
- **K-Nearest Neighbors:** Best at predicting failure stress (y_2), likely due to sensitivity to local variations (e.g. raster angle).
- **Gaussian Process Regression:** Useful for uncertainty quantification, but struggled with extreme values due to poor extrapolation.
- **Raster angle as input:** Improved model accuracy, especially for KNN; helped uncover clusters tied to print orientation.

Reference

Nasrin, T., Pourali, M., Pourkamali-Anaraki, F., & Peterson, A. M. (2023). Active learning for prediction of tensile properties for material extrusion additive manufacturing. Scientific reports, 13(1), 11460.