Artificial Intelligence and Machine Learning in Printed Electronics Design

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Why we are doing this project

- This project aims to improve the precision and predictability of printed electronics via a combination of feature-based and image-based machine learning models for an AI optimization scheme acting upon various printing process parameters.

- By using AI and machine learning, we can optimize the accuracy of printed electronics, thus reducing the waste caused by actual experiments while boosting the efficiency and versatility of the technology.

- By using the actual test data, we can train the machine learning model to input the lithography and output the actual electrical characteristics of the printed device.

How we obtain the dataset

- We design mask and use it to print resistors with different parameters on NanoDimension DragonFly IV 3D printer.

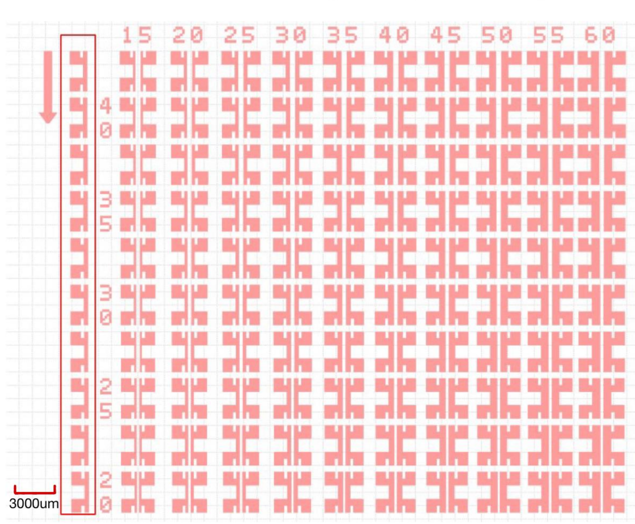
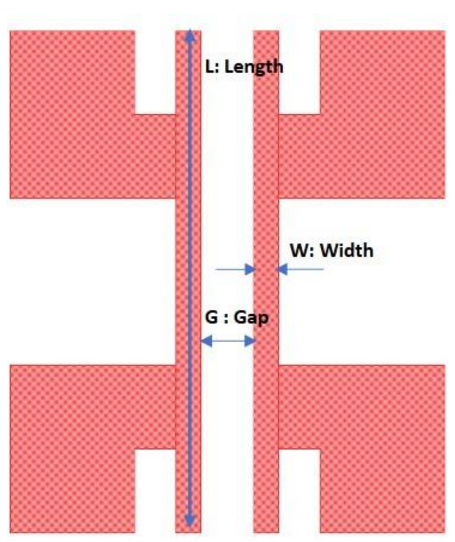


Figure: (Left) Layout of printed resistor pairs for testing; (Right) DragonFly IV 3D printer used for fabrication.

- In printed electronics fabrication, R2 data modeling focuses on two key printer parameters: Dynamic Top Oven (DTO) speed (0 mm/s, 200 mm/s, 400 mm/s) and Tray Temperature (120°C, 160°C, 175°C) during the drying phase.



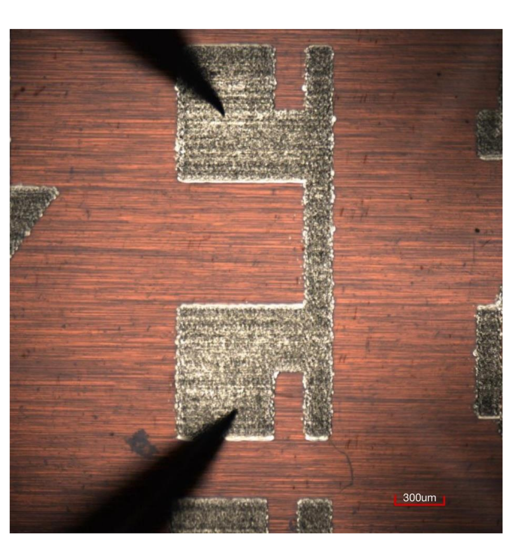


Figure: (Left) Schematic of unit resistor pair showing length (L), width (W), and gap (G); (Right) Image of physical printed resistor under four-probe measurement.

- Measurement Procedure: Record both target and measured widths/gaps. Then, perform four-probe measurements to obtain voltage and current, from which resistance and conductance are calculated.

Acknowledgement

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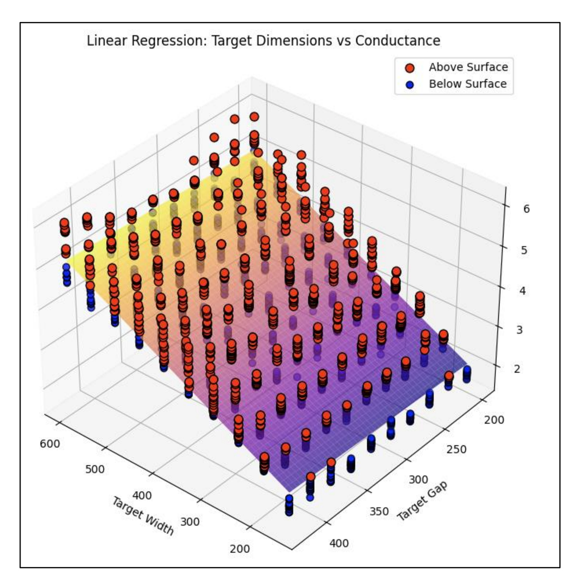
Training Process and Results of R1 Model

- **Model Setup: The R1 model used width and gap as input features, including both target layout values and actual measured values.**
- **Output Variable: The model was trained to predict the electrical behavior. Specifically, conductance was measured to evaluate how easily current flows through the structure.**
- **Model Exploration: Varius modeling techniques was tested to determine the most accurate fit for the conductance data. This includes Linear Regression, Random Forest, and Multilayer Perceptron**
- **Motivations: (1) Identify the most accurate model; (2) Test the expected linear relationship between conductance and width.**
- **Key Result: Linear regression outperformed all other models, showing a strong fit and confirming a linear pattern. This is consistent with the expected linear relationship.**
- **Input Accuracy: Compared errors from target vs. measured inputs to evaluate their impact on model performance. The umbrella plots show no significant error patterns.**

- **Models**

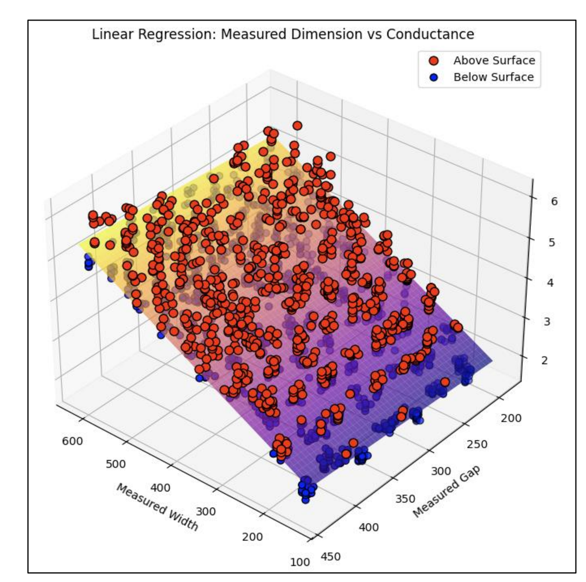
Model Name	Performance (R^2)	Do we use it	Why
Multilayer Perceptron	0.9056(Target)/ 0.90054(Measured)	NO	Over fitting
Random Forest	0.9120(Target)/ 0.95112(Measured)	NO	Over fitting
Linear Regression	0.8844(Target)/ 0.88079(Measured)	YES	Met expectations

- **Target**



Linear Regression Model
Conductance = 0.9314 + (0.0064 * Target_Width) + (0.0009 * Target_Gap)

- **Measured**



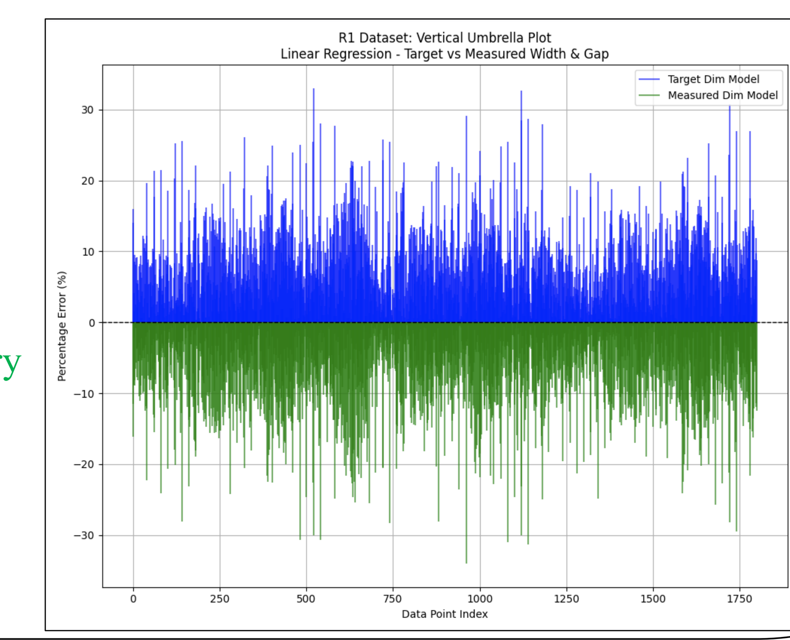
Linear Regression Model
Conductance = 0.8705 + (0.0066 * Measure_Width) + (0.0009 * Measure_Gap)

- **Error: Target VS Measured**

Umbrella Plot

Blue: Target Geometry

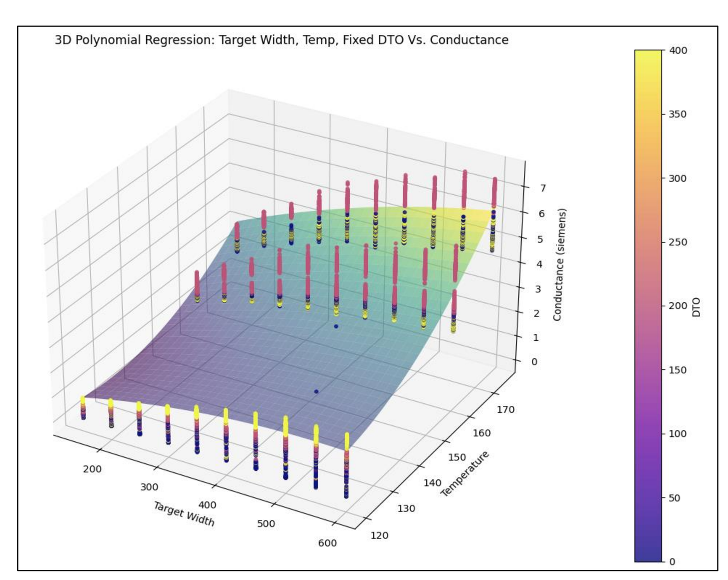
Green: Measured Geometry



Training Process and Results of R2 Model

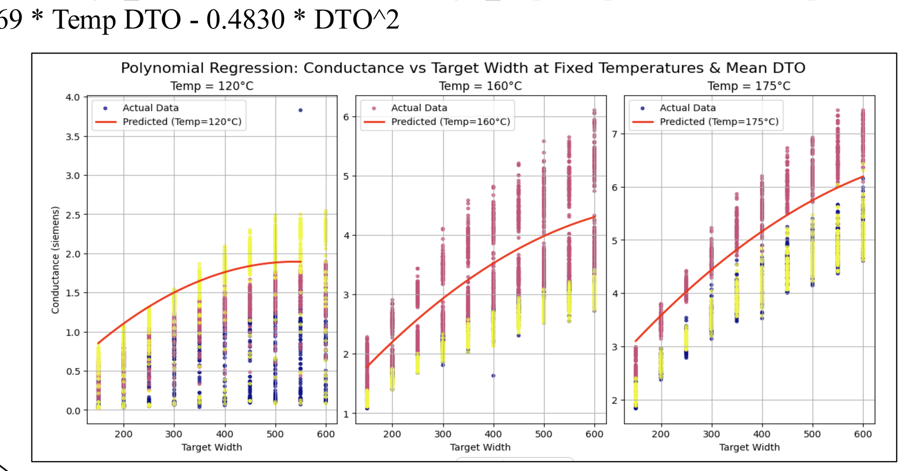
- **For the R2 model, expanded input features: Incorporated width, gap, DTO, and temperature as additional inputs; both target and measured values for width and gap were included to enrich the dataset.**
- **Model Evaluation: Tested multiple machine learning approaches (Linear Regression, Polynomial Regression, etc.), and polynomial regression delivered the highest predictive accuracy for conductance.**
- **Model Optimization with Least Absolute Shrinkage and Selection Operator (LASSO): Observed redundancy in polynomial terms; applied input scaling and LASSO regression enhance interpretability.**
- **Input Source Comparison: Compared model prediction errors when using target vs. measured input values to evaluate their impact on model performance.**

- **Target**



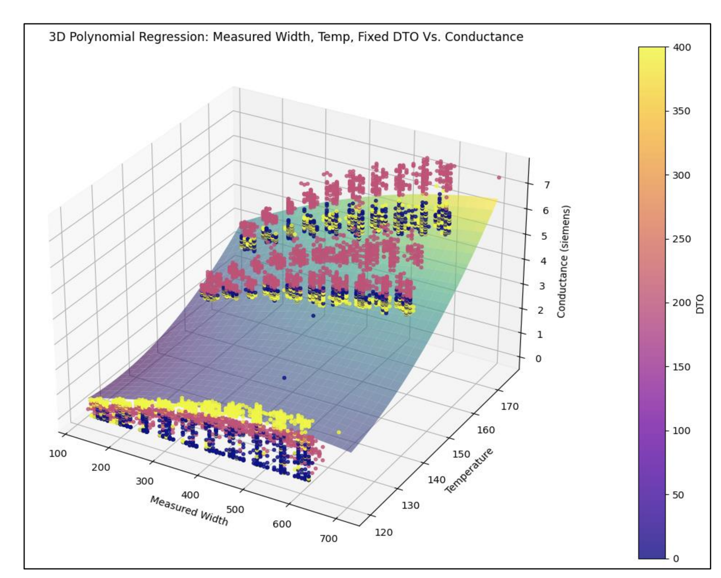
Polynomial Regression Model (LASSO)

Conductance = 2.8059 + 0.7041 * Target_Width + 0.0128 * Target_Gap + 1.5406 * Temp + 0.0904 * DTO - 0.1281 * Target_Width^2 + 0.2565 * Target_Width Temp + 0.0207 * Target_Width DTO + 0.0097 * Target_Gap Temp + 0.5242 * Temp^2 - 0.1569 * Temp DTO - 0.4830 * DTO^2



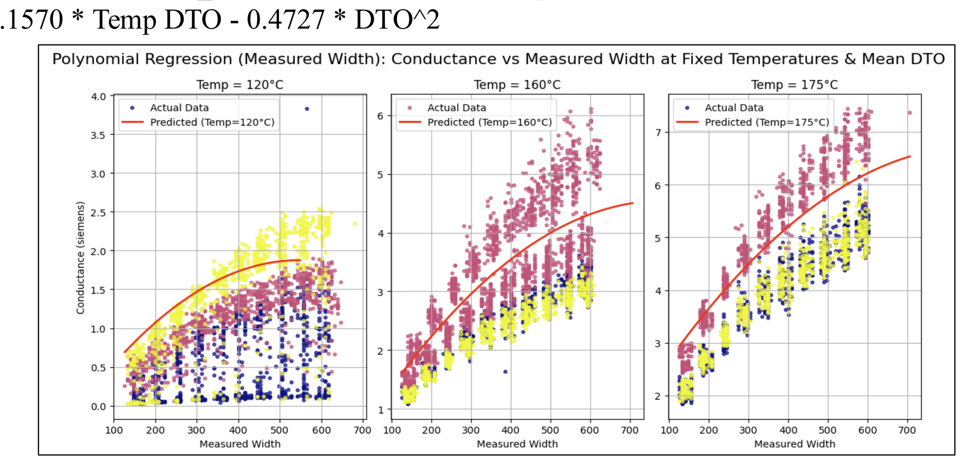
Slice plot of target

- **Measured**



Polynomial Regression Model (LASSO)

Coductance = 2.8017 + 0.7048 * Measure_Width + 0.0123 * Measure_Gap + 1.5678 * Temp + 0.0914 * DTO - 0.1287 * Measure_Width^2 + 0.2490 * Measure_Width Temp + 0.0212 * Measure_Width DTO + 0.5304 * Temp^2 - 0.1570 * Temp DTO - 0.4727 * DTO^2



Slice plot of measured

- **Models**

Model Name	Performance (R^2)	Do we use it	Why
Linear Regression	0.7876(Target)/ 0.79(Measured)	NO	Relatively Inaccurate
Multilayer Perceptron	0.825(Target)/ 0.76(Measured)	NO	Relatively Inaccurate
Random Forest	0.9519(Target)/ 0.9839(Measured)	NO	Over Fitting
Polynomial Regression	0.9214(Target)/ 0.922(Measured)	NO	Redundant Variables
Polynomial Regression(Lasso)	0.9207(Target)/ 0.9213(Measured)	YES	Met Expectations

- **Error: Target VS Measured**

Blue: Target Geometry

Green: Measured Geometry