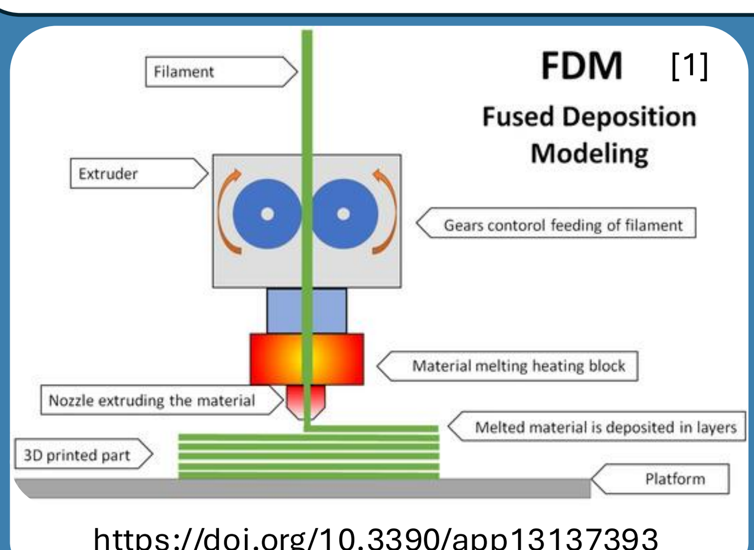
AI-Powered Thermal Fingerprinting:
Predicting PLA Tensile Strength Through Schlieren Imaging

Introduction & Previous Approaches



https://doi.org/10.3390/app13137393

Market Trends:
- 59% of AM uses FDM
- End use parts: 23.7% annual growth
- Market Projection: $3.3B - $8.4B by 2031

Thermal Environment is Important:
- Temperature controls polymer chain mobility and reptation
- Environmental conditions (ambient temperature, airflow, humidity) significantly impact properties

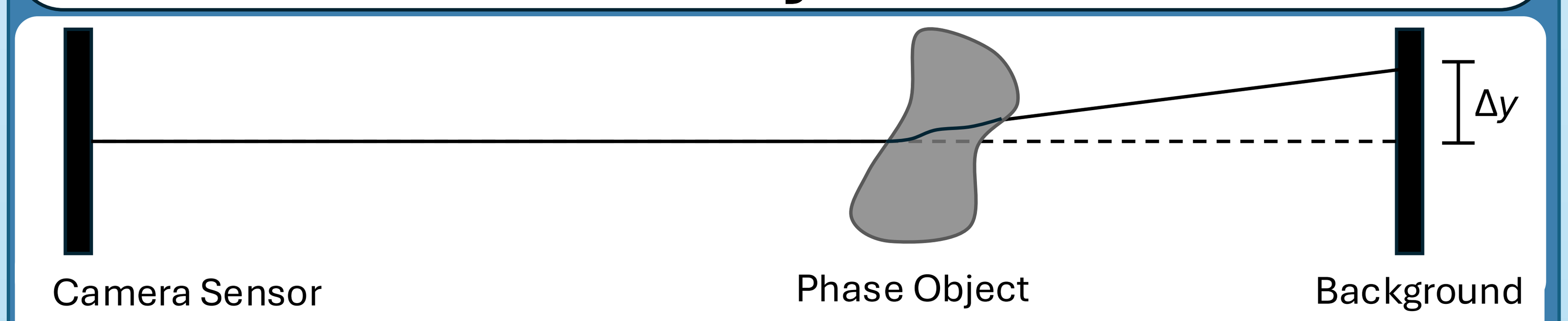
Fused Deposition Modeling (FDM) is Unpredictable >10% strength variations in "identical" parts (same print speed, layer height, etc.)

Mordor Intelligence, 2025

Previous Approaches Fail to Capture Important Features:
- *Infrared Thermography (IR):* Non-contact, real-time, only measures surface temp, $1,000-50,000
- *Ultrasonic Testing (UT):* Can reveal internal defects, requires tool to be touching, $1,000-20,000
- *X-ray Tomography (XCT):* Very slow, difficult for in-situ. Reveals precise internal structures, $100,000-2,000,000
- *ML Model:* Doesn't account for environment

Reliability is *critical* as applications expand toward end-use parts.

BOS System



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Background-Oriented Schlieren Imaging
- Captures small refractions of light in the air caused by changes in density
- Refractions are tracked to reconstruct a density gradient
- Creates a *visualization of airflow*

Cost Not Including Camera: $50

Cost Including Camera: ~$1,050

Project Overview

Introducing... *thermal fingerprinting*

Imagine real-time, non-contact quality control that accurately assesses tensile strength from simply taking photos.

First-ever application of Schlieren to polymer additive manufacturing.

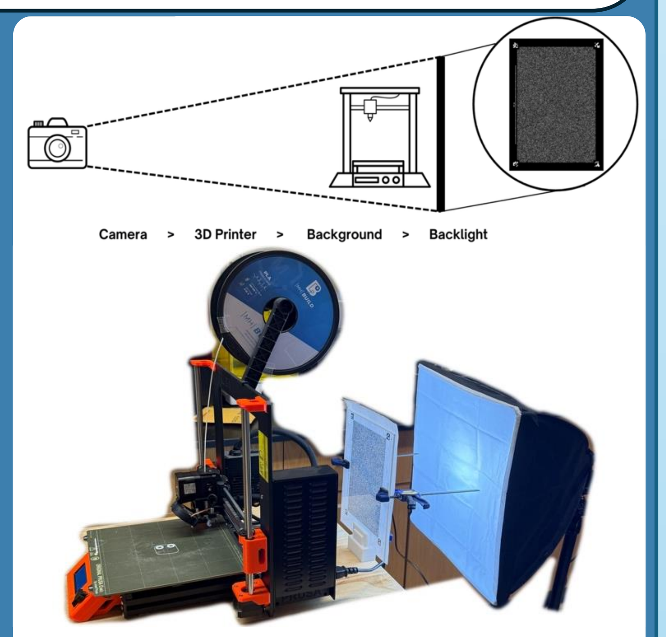

Image taken by finalist, 2025;
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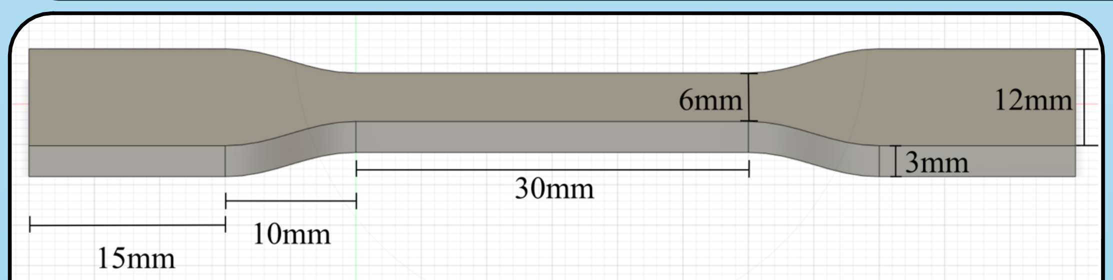
Methods



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30 standard dog-bone specimens were printed across 6 different conditions. (n=5 per condition)

All specimens were printed with constant parameters:
- 20% Infill
- 60°C Bed Temperature, 200° Nozzle Temperature
- 50 mm/s Print Speed

Code	Condition	Description
A	Maximum Cooling	Two hairdryers operated on "maximum cooling" settings.
B	Moderate Cooling	Two hairdryers operated on "moderate cooling" settings.
C	Standard (Control)	Only the printer's internal fan provided airflow.
D	Asymmetric	One hairdryer operated on "maximum heating", other on "maximum cooling".
E	Moderate Heating	Two hairdryers operated on "reduced heat" settings.
F	Maximum Heating	Two hairdryers operated on "maximum heating" settings.

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BOS Images Taken During Printing

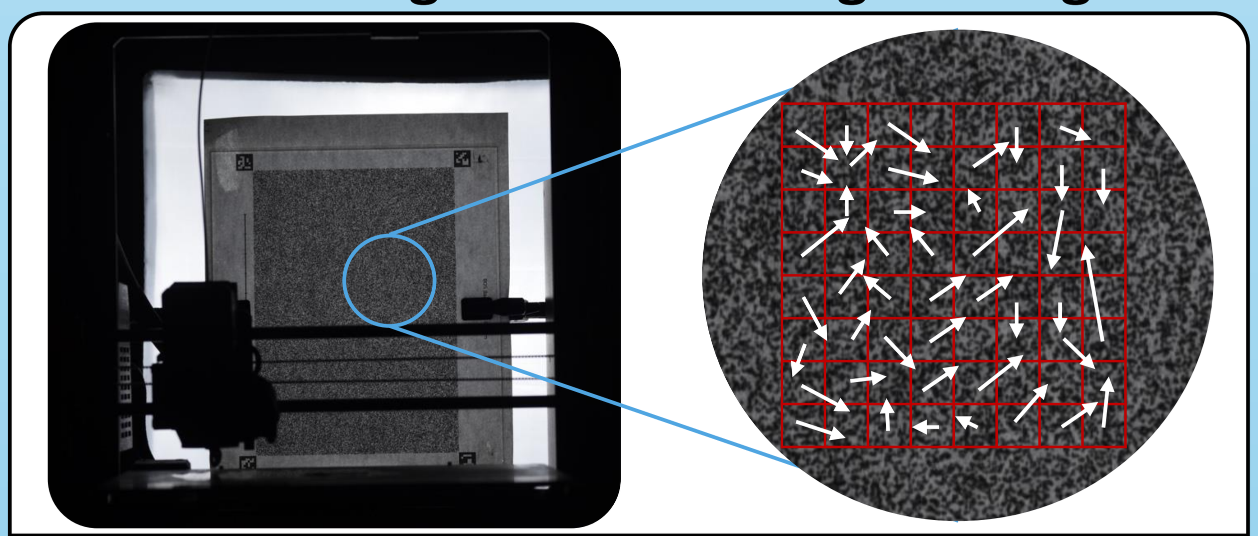
Image taken by finalist, 2025; Figure created by finalist using PowerPoint, 2026

Schlieren Data Exported to CSV File

Header	Description
x	Pixel x-coordinate
y	Pixel y-coordinate
u	Horizontal flow component
v	Vertical flow component
magnitude	Flow magnitude (gradient)
angle	Flow direction
analysis_region	In white region mask (0 or 1)

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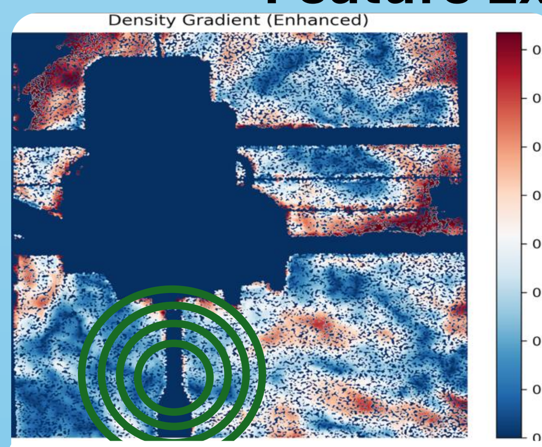
Feature Extraction



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Radial Zones:
Zone 1: 0-20%
Zone 2: 20-40%
Zone 3: 40-60%
Zone 4: 60-100%

- Radial zones: Mean, std, density in concentric rings
- General stats: Print, near-field, far-field magnitude
- Asymmetry: Horizontal/vertical gradients, L-R ratios
- Temporal evolution across 9 layers

Each specimen was tested with an ADMET Tensile Testing machine.

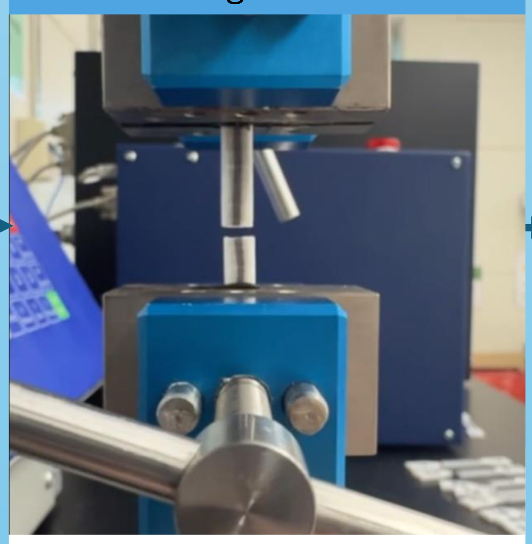
Image taken by finalist, 2025

Model Training and Testing

- Upload Schlieren CSV
- Upload Tensile Testing CSV
- Upload Print Center CSV
- Parse through data
  - 270 Schlieren files
- Match each Schlieren data to Tensile and Print Center data for each specimen
- Predict condition classification
- Predict tensile strength (MPa)

Model Design

Classification Model (Cooling Condition)

Model	Why	# of Trees	Depth
Random Forest	Handles non-linear patterns well, robust	200	10
XGBoost	Gradient boosting, high performance	200	6

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Purpose: Identify environmental printing condition
Feature reduction: 1847 → 40 features using SelectKBest
Majority voting ensemble: Random Forest + XGBoost predictions combined

Regression Model (Tensile Strength)

Model	Why	# of Trees	Depth
Random Forest	Handles non-linear patterns well, robust	200	10
XGBoost	Gradient boosting, high performance	200	6
Gradient Boosting	Sklearn, diverse ensemble member	200	5

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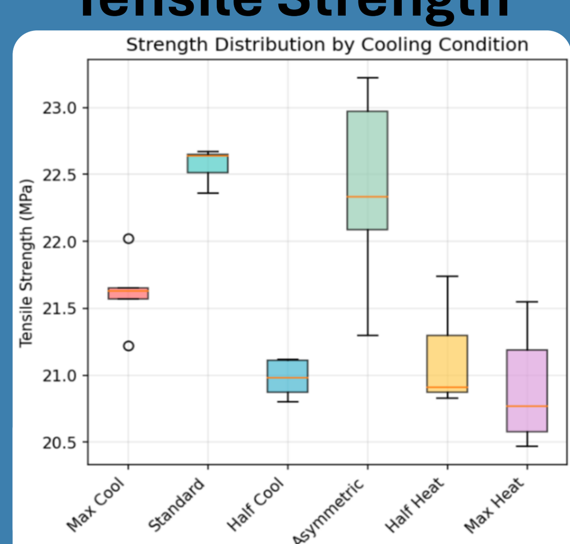
Purpose: Predict ultimate tensile strength (MPa)
Feature selection: Moderate-importance features
Averaging strategy: Equal weight to all three model predictions

Results

Tensile Strength



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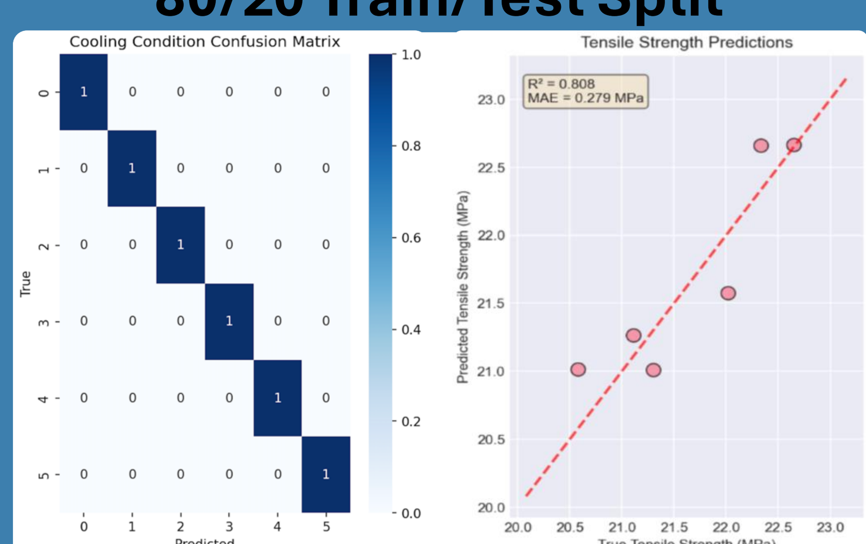
- 8.3% difference in strength between conditions
- Most conditions showed tight consistency (IQR <2% of median), except Asymmetric condition (IQR=4.25% of median)

80/20 Train/Test Split

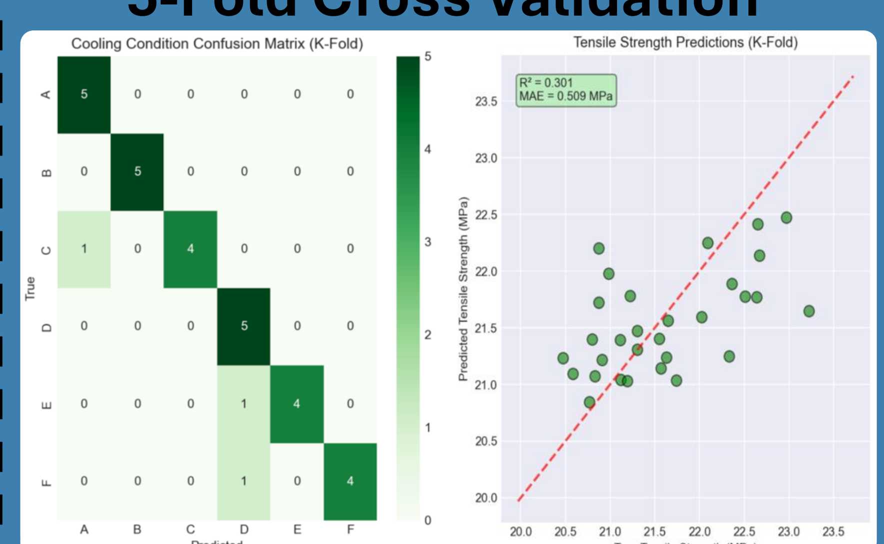


Figures created by finalist using Python, 2025

Tensile Strength Regression:
R^2 = 0.808
MAE= 0.279 MPa (*1.3% of mean, 10% of variability*)

Classification:
100% Accuracy

5-Fold Cross Validation



Figures created by finalist using Python, 2025

Tensile Strength Regression:
R^2 = 0.301
MAE= 0.509 MPa (*2.3% of mean, 18.5% of variability*)

Classification:
90% Accuracy

Limitations & Future Work

Limitations & Path Forward:
- n=30 limits generalization (cross validation R^2=0.301)
- Scale to 200+ specimens across multiple materials
- *Project provides methodical foundation for entirely new territory*

Manufacturing Impact:
- Real-time quality prediction without stopping production
- <$2,000 system cost democratizes advanced quality assurance
- Reduces waste from previously-undetected defects

Key References

[1] Przekop, R. et al. (2023). Liquid for Fused Deposition Modeling Technique (L-FDM)—A Revolution in Application Chemicals to 3D Printing Technology: Color and Elements. MDPI. https://doi.org/10.3390/app13137393 [2] Mordor Intelligence. (2025). Fused Deposition Modeling (FDM) Technology 3D Printer Market Size & Share Analysis - Growth Trends and Forecast (2026 - 2031). https://www.mordorintelligence.com/industry-reports/fused-deposition-modeling-technology-3d-printer-market [3] Protolabs. (2024). 3D Printing Trend Report 2024. https://www.protolabs.com/resources/guides-and-trend-reports/3d-printing-trend-report/ [4] Carelabs. (2017). Why is Electrical Infrared Thermography Inspection Important?. https://carelabz.com/electrical-infrared-thermography-inspection-important/ [5] Tec-Science. (2018). Ultrasonic testing (UT). https://www.tec-science.com/material-science/material-testing/ultrasonic-testing-ut/ [6] Dong, K. et al. (2024). Projection-Angle-Sensor-Assisted X-ray Computed Tomography for Cylindrical Lithium-Ion Batteries. MDPI. https://doi.org/10.3390/s24041102 [7] Pandey, A. (2024). Farneback Algorithm. Medium. https://medium.com/pythons-gurus/farneback-algorithm-50682b8aa2eb [8] Golhin, A. (2021). The Influence of Wedge Angle, Feedstock Color, and Infill Density on the Color Difference of FDM Objects. MDPI. doi.org/10.2352/J.ImagingSci.Technol.2021.65.5.050408

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