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Tensile Testing and Mechanical Property Prediction of 3D Printed PLA Using FEA and Machine Learning

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***Abstract:** This paper presents an integrated methodology combining physical tensile testing, finite element analysis (FEA), and machine learning (ML) to evaluate and predict the mechanical behaviour of 3D printed polylactic acid (PLA). ASTM D638 Type I specimens were fabricated using a Raise3D E2 printer and tested with an INSTRON 5582 Universal Testing Machine. Numerical simulations were performed using ANSYS Mechanical, and tensile strength was predicted using an Elastic Net Regression model trained on publicly available data. The proposed hybrid approach demonstrates effective parameter optimization and provides valuable insights into the mechanical performance of PLA components produced via additive manufacturing.*
***Keywords:** 3D Printing, PLA, Tensile Testing, FEA, Machine Learning*

I. INTRODUCTION

The mechanical properties of engineering materials play a critical role in determining the structural integrity, geometry, and overall design of manufactured components. Among these, tensile strength is particularly significant and is typically assessed through uniaxial tensile testing. This testing method produces a stress–strain curve, enabling the extraction of key material properties such as Young's modulus, yield strength, and elongation at break.

Additive manufacturing (AM), especially fused deposition modelling (FDM), has witnessed rapid growth in industries such as aerospace, biomedical engineering, and consumer products. Its ability to fabricate intricate geometries with high customization and minimal material wastage makes it a preferred manufacturing method [1], [2]. Polylactic Acid (PLA), a biodegradable thermoplastic derived from renewable sources like corn and sugarcane, is widely used in FDM due to its favourable printability, mechanical strength, and eco-friendliness [3].

To investigate PLA's mechanical performance, three tensile specimens were fabricated following the ASTM D638 Type I standard using a Raise3D E2 printer. Mechanical testing was conducted using an INSTRON 5582 Universal Testing Machine (UTM). While experimental testing yields accurate results, it can be time-consuming and costly due to repeated design-test iterations [2].

To overcome these limitations, a machine learning (ML) model was implemented to predict tensile strength based on critical printing parameters. The model was trained on a publicly available dataset from Kaggle [4] and validated using experimental data. Additionally, finite element analysis (FEA) was conducted in ANSYS Mechanical to simulate stress distribution under uniaxial loading and to correlate with observed failure regions [5].

This multidisciplinary approach—integrating experimental testing, numerical simulation, and data-driven prediction—offers an efficient and robust methodology for characterizing and optimizing the mechanical behaviour of 3D-printed PLA components.

II. SPECIMEN DESIGN AND MODELING

A. 2D CAD Design

To ensure consistency and adherence to standardized tensile testing protocols, the specimen geometry was designed according to the ASTM D638 Type I specifications [2]. This standard defines a dogbone-shaped profile commonly used for evaluating the mechanical properties of rigid plastics and enables meaningful comparison between different materials [5].

The 2D drawing was created in AutoCAD 2024 with precise dimensional control. Key geometric features—including gauge length, shoulder width, grip section, and fillet radius—were carefully dimensioned to minimize variability that could influence stress–strain measurements. The complete dimensions are provided in Table I.

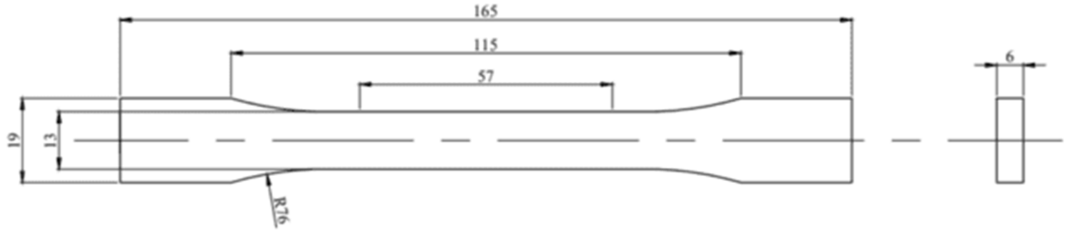

Fig. 1 2D Drawing of ASTM D638 Type I Standard Specimen

TABLE I
THE COMPLETE DIMENSIONS OF THE SPECIMEN

Dimension	Length (in mm)
Overall length	165
Gap between grips	115
Gauge Length	57
Inner width	13
Outer width	19
Thickness	6
Fillet Radius	76

B. 3D CAD Design

The 3D model was developed in SolidWorks using the exact dimensions from the 2D drawing. SolidWorks was selected for its ability to create precise parametric models suitable for both simulation and fabrication.

Two output formats were generated from the final model:

1) *IGS File:* Used for finite element analysis in ANSYS Mechanical. This format preserves geometric detail, enabling accurate meshing and stress distribution analysis [6].
2) *STL File:* Exported for slicing and 3D printing. The model was saved in STL format, producing a triangulated mesh compatible with most slicing software.

This dual-purpose modelling approach ensured that the same geometry was used in both physical experiments and virtual simulations, allowing for direct validation of results and minimizing discrepancies between modelled and printed specimens [7].

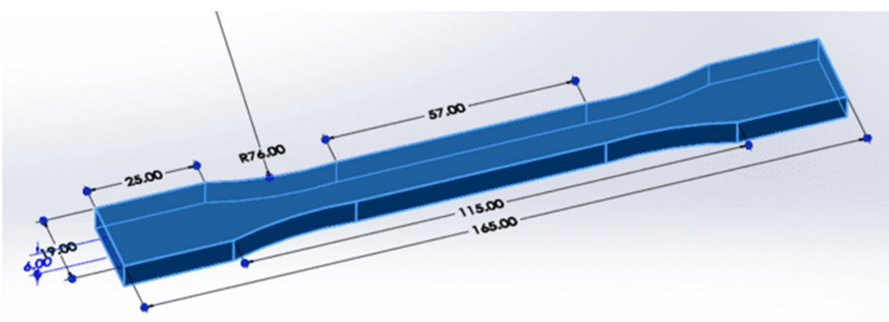

Fig. 2 3D model of ASTM D638 Type - 1 standard with dimensions

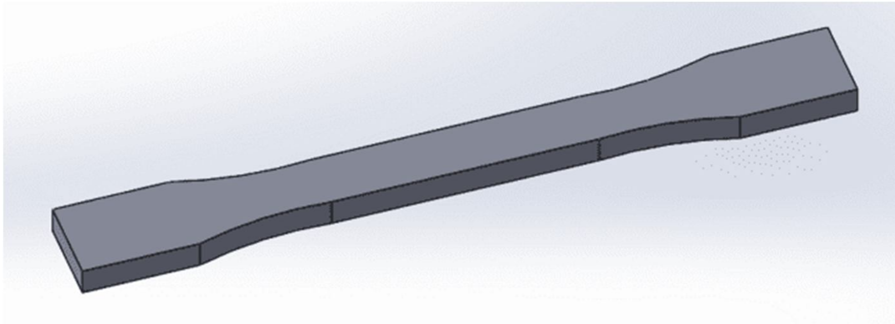

Fig. 3 Final 3D model of specimen

III. 3D PRINTING PARAMETERS AND FABRICATION

A. Slicing and Settings

Following the development of the 3D model in SolidWorks, the geometry was exported as an STL file and imported into IdeaMaker, the slicing software provided by Raise3D. This step converted the 3D geometry into G-code, the machine-readable format required for 3D printing.

During slicing, key print parameters were defined. These parameters significantly affect the mechanical behaviour of the printed specimens, including tensile strength, Young's modulus, and strain at break [4], [5]. Maintaining strict control over these parameters ensured dimensional precision and mechanical consistency across all samples.

All three tensile specimens were sliced using identical parameters to maintain uniformity in the fabrication process. This minimized variability and ensured that the CAD geometry was faithfully translated into physical form.

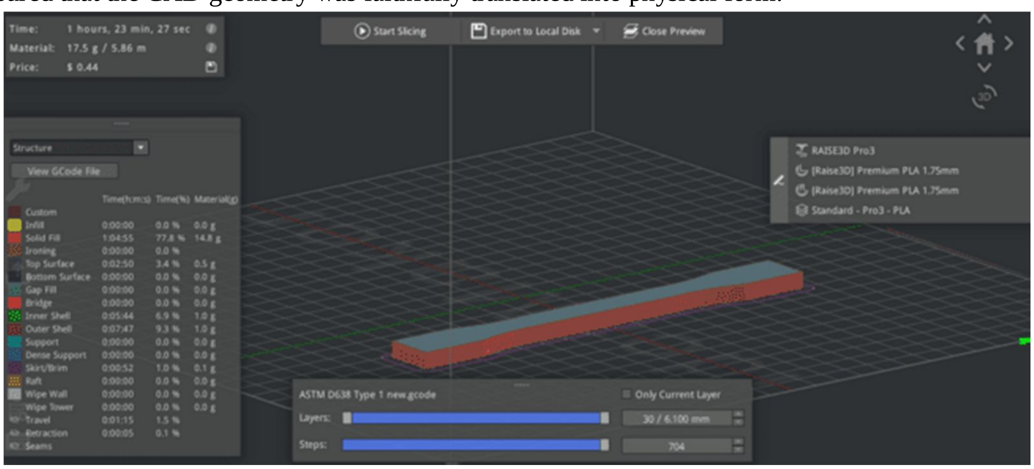

Fig. 4 Slicing of STL file with defined print parameters in IdeaMaker

TABLE II

3D PRINTING PARAMETERS USED FOR SPECIMEN FABRICATION

Print Parameter	Specification
Layer height	0.2 mm
Wall Thickness	0.8 mm
Infill Density	100%
Infill Pattern	Honeycomb
Nozzle Temperature	205℃

Bed Temperature	45°C
Print Speed	70 mm/s
Material	PLA

B. Printing Using the Raise3D E2 Printer

The finalized G-code was transferred to the Raise3D E2 printer for specimen fabrication.

1) *Print Setup:* All specimens were printed using PLA filament via the left extruder only, while the right extruder remained inactive. This configuration ensured consistent material flow and eliminated variability from nozzle switching.
2) *Print Time and Environmental Control:* Each specimen took approximately 1.5 hours to fabricate. The printer's enclosed build chamber and thermal regulation system were instrumental in achieving dimensional stability and minimizing internal residual stresses during the solidification process [6].

These controlled printing conditions contributed to the reliability and repeatability of the specimens for subsequent mechanical testing.

Fig. 5 RAISE3D E2 printer

Fig. 6 Final 3D Printed ASTM D638 Type I Tensile Specimen

IV. TENSILE TESTING USING INSTRON 5582 UTM

A. Testing Protocol

Tensile testing was conducted on all three specimens using the INSTRON 5582 Universal Testing Machine (UTM) located in the Department of Mechanical Engineering. Testing adhered to the ASTM D638 Type I standard [2], ensuring uniform methodology and comparability of results.

Prior to testing, the specimen thickness was measured using a micrometre and found to be 6.1 mm—slightly above the nominal 6.0 mm value—due to an initial layer height setting of 0.3 mm during fabrication.

All tests were performed under identical conditions:

- Gauge Length: 57 mm
- Maximum Load Capacity: 5 kN
- Strain Rate: 0.1126 mm/s

These conditions were held constant to ensure consistency across samples. The collected data was used to derive key mechanical properties including Young's modulus (E), yield strength (Syt), ultimate tensile strength (Sut), and strain at break.

Fig. 7 INSTRON 5582 UTM Used for Tensile Testing

B. Experimental Results and Analysis

Tensile tests were performed on three PLA specimens, and their mechanical behaviour was characterized using stress–strain and load–extension curves. The extracted mechanical properties for each sample are presented below.

1) Sample 1: Tensile stress (MPa) vs Tensile strain (%) curve:

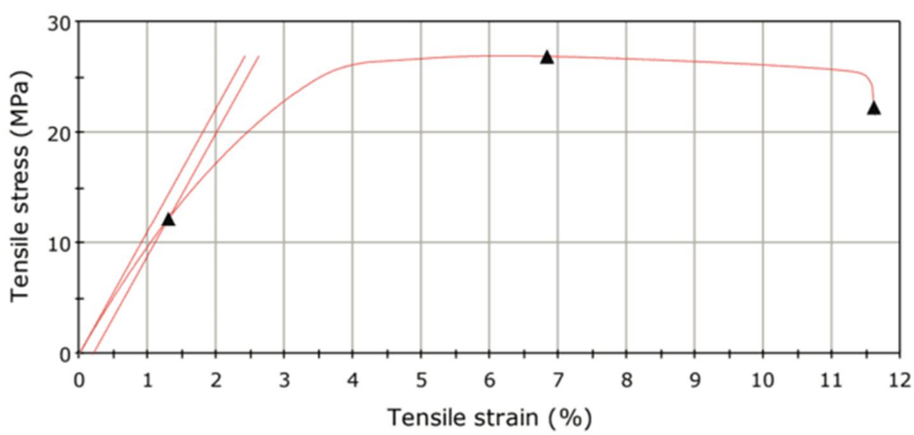

Fig. 8 Tensile Stress vs. Strain Curve for Sample 1

Load (KN) vs Tensile extension (mm) curve:

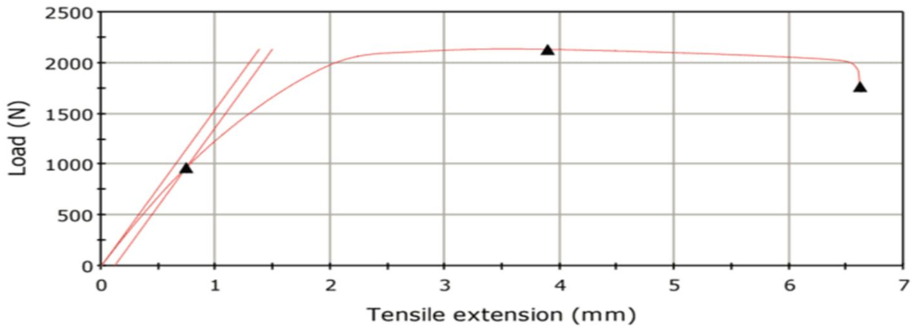

Fig. 9 Load vs. Extension Curve for Sample 1

TABLE III
MECHANICAL PROPERTIES OF SAMPLE 1

Material Property	Specification
Modulus of Elasticity (E)	1110 MPa
Yield Strength (S_{yt})	12.24 MPa
Ultimate Tensile Strength (S_{ut})	26.84 MPa
Tensile strain at break	11.60%

2) *Sample 2:* Tensile stress (MPa) vs Tensile strain (%) curve:

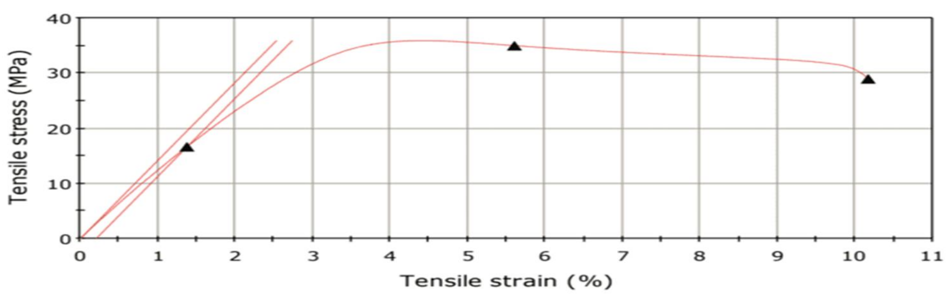

Fig. 10 Tensile Stress vs. Strain Curve for Sample 2

Load (KN) vs Tensile extension (mm) curve:

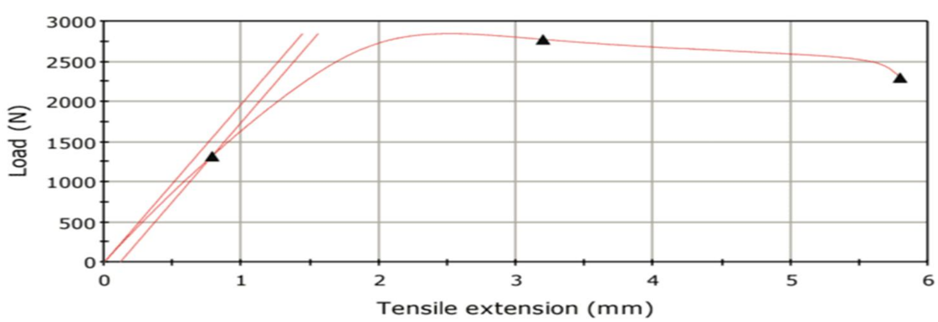

Fig. 11 Load vs. Extension Curve for Sample 2

TABLE IV
MECHANICAL PROPERTIES OF SAMPLE 2

Material Property	Specification
Modulus of Elasticity (E)	1415 MPa
Yield Strength (S_{yt})	16.68 MPa
Ultimate Tensile Strength (S_{ut})	34.95 MPa
Tensile strain at break	10.15%

3) *Sample 3:* Tensile stress (MPa) vs Tensile strain (%) curve:

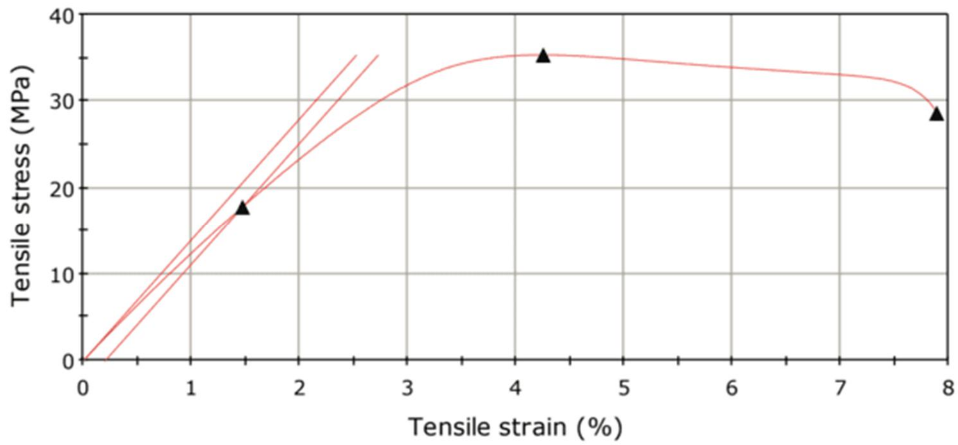

Fig. 12 Tensile Stress vs. Strain Curve for Sample 3

Load (KN) vs Tensile extension (mm) curve:

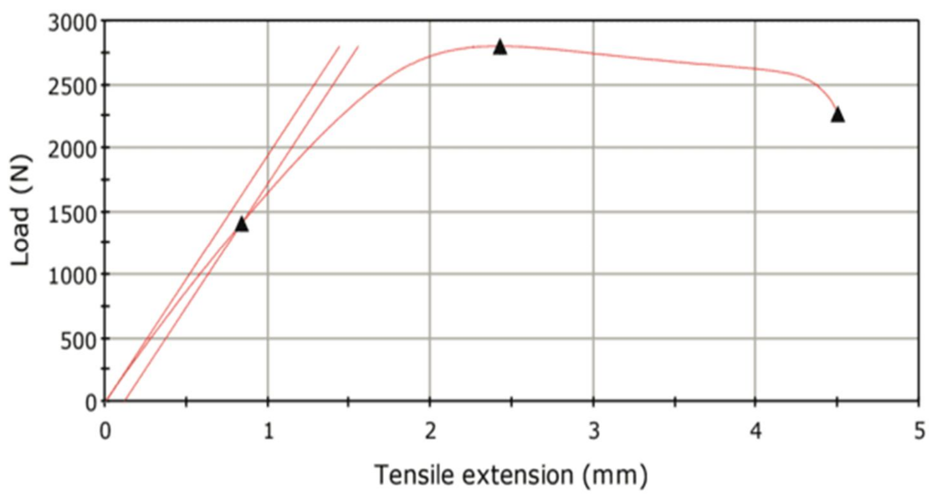

Fig. 13 Load vs. Extension Curve for Sample 3

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TABLE V
MECHANICAL PROPERTIES OF SAMPLE 3

Material Property	Specification
Modulus of Elasticity (E)	1399 MPa
Yield Strength (S_{yt})	17.77 MPa
Ultimate Tensile Strength (S_{ut})	35.28 MPa
Tensile strain at break	7.88%

C. Comparative Results

1) *Combined Stress–Strain Analysis:* To assess the mechanical performance across all specimens, a comparative stress–strain plot was generated, highlighting differences in stiffness, strength, and elongation behaviour.

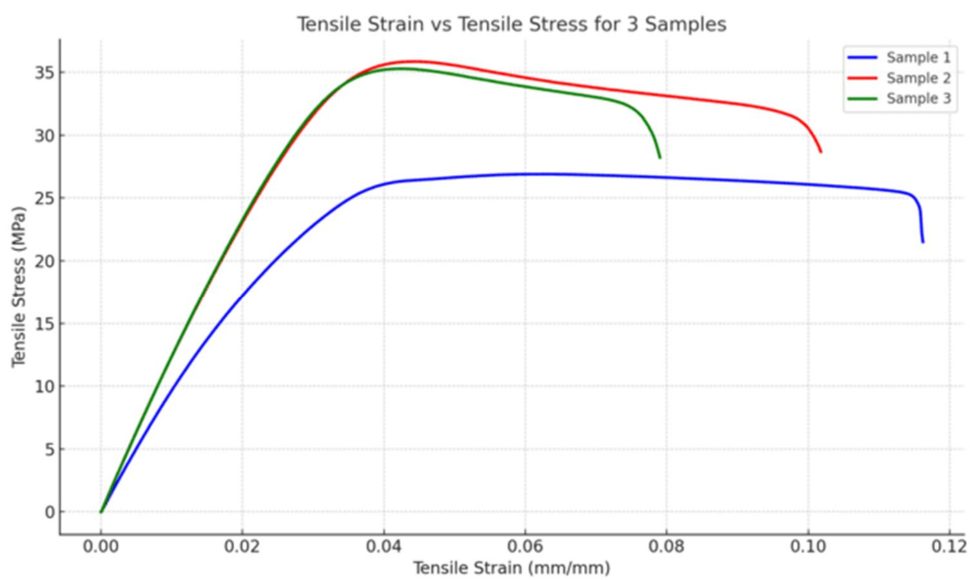

Fig. 14 Combined Stress–Strain Curve for All Samples

2) *Summary of Mechanical Properties:* A consolidated table presents the key mechanical properties of all three samples along with their average values.

TABLE VI
SUMMARY OF MECHANICAL PROPERTIES

Sample No.	Modulus of Elasticity (E) (MPa)	Yield Strength (S_{yt}) (MPa)	Ultimate Tensile Strength (S_{ut}) (MPa)	Tensile strain at break (%)
1	1110	12.24	26.84	11.60
2	1415	16.68	34.95	10.15
3	1399	17.77	35.28	7.88
Mean	1308	15.56	32.35	9.87

3) *Fracture Surface Observations:* Post-fracture analysis revealed that all specimens failed at the fillet region, which coincided with the area of maximum stress predicted by simulation.

Fig. 15 Fractured Specimens Post-Testing

4) *Key Conclusions from Tensile Testing:*

Material Behaviour: PLA exhibited primarily brittle characteristics, as indicated by strain-at-break values below 15%, consistent with literature findings [3].

Average Mechanical Properties:

- Modulus of Elasticity: 1308 MPa
- Yield Strength: 15.56 MPa
- Ultimate Tensile Strength: 32.35 MPa

Fracture Analysis: All failures occurred at the fillet radius, confirming it as the critical stress concentration zone- corroborating both theoretical expectations and FEA results.

Visual Strain Indicators: A noticeable colour transition from dark to light blue was observed during deformation, suggesting localized yielding and material strain.

Specimen-Specific Observations:

- Sample 1 showed minor anomalies, possibly due to surface imperfections or microcracks during printing.
- Sample 3 exhibited reduced elongation, likely caused by print-induced warping or uneven extrusion.

V. MACHINE LEARNING-BASED TENSILE STRENGTH PREDICTION

A. Dataset and Features

To augment the experimental findings, a machine learning (ML) model was developed to predict the tensile strength of 3D-printed PLA specimens based on key printing parameters. The model was trained on a publicly available dataset from Kaggle [4], originally contributed by the Mechanical Engineering Department of Selçuk University. The dataset comprises approximately 50 records, each representing a unique set of 3D printing parameters with corresponding tensile strength values.

The input features used for model training included:

- Layer Height (mm)
- Wall Thickness (mm)
- Infill Density (%)
- Infill Pattern
- Nozzle Temperature (°C)
- Bed Temperature (°C)
- Print Speed (mm/s)
- Material Type
- Fan Speed (%)

The output variable (target) was the tensile strength in MPa. A correlation matrix was generated to examine inter-feature relationships.

```
data.corr()["tension_strength"].sort_values()

nozzle_temperature    -0.405908
print_speed           -0.264590
fan_speed             -0.252883
bed_temperature       -0.252883
infill_pattern         0.009054
material               0.289726
layer_height           0.338230
infill_density         0.358464
wall_thickness         0.399849
tension_strength       1.000000
Name: tension_strength, dtype: float64
```

Fig. 16 Correlation Coefficients of Input Features

B. Model Details

1) *Observations from Correlation Analysis:*

- Nozzle temperature showed a negative correlation with tensile strength, indicating that excessive heat may reduce inter-layer bonding.
- Wall thickness and infill density demonstrated strong positive correlations with tensile strength, highlighting their influence on structural integrity—consistent with prior studies [5], [7].

2) *Model Selection and Training:* An Elastic Net Regression model was selected for its ability to manage multicollinearity and leverage both L1 (Lasso) and L2 (Ridge) regularization. The dataset was split into training (90%) and testing (10%) subsets. Standardization was applied to ensure feature uniformity.

3) *Hyperparameter Tuning:*

- Model: Elastic Net Regression
- Regularization Strength (Alpha): 1
- L1 Ratio: 1 (pure Lasso behaviour)

4) *Model Performance:* The model was evaluated using standard regression error metrics:

- Mean Absolute Error (MAE): 2.09 MPa
- Root Mean Squared Error (RMSE): 2.60 MPa

When evaluated using the actual print parameters from this study (see Table II), the model predicted a tensile strength of 30.71 MPa, closely matching the experimental mean of 32.35 MPa (5.07% deviation).

5) *Implications and Availability:* This demonstrates the capability of ML to serve as a predictive design tool, reducing the number of physical prototypes required. The complete source code and dataset processing pipeline are publicly available at: *GitHub Repository – AngadRiat/3d_print*

VI. FINITE ELEMENT ANALYSIS IN ANSYS MECHANICAL

A. Simulation Setup

Finite Element Analysis (FEA) was conducted in ANSYS Mechanical to simulate the stress distribution in the PLA tensile specimen and validate the experimental results. The model geometry was imported in IGES format from SolidWorks.

1) *Observations from Correlation Analysis:* PLA was modelled as an isotropic linear elastic material using properties derived from experimental Sample 2.

TABLE VII
MATERIAL PROPERTIES USED IN FEA SIMULATION

Material Name	PLA
Material Type	Isotropic Elasticity
Young's Modulus (E)	1415 MPa (From Sample 2)
Poisson's Ratio	0.36

2) *Meshing and Boundary Conditions:*
- A fine mesh was applied using curvature-based refinement to resolve stress gradients near fillet regions.
- Fixed Support: Applied to one grip end to simulate fixture conditions.
- Force Vector: A tensile load of 2711 N was applied at the opposite end to simulate elastic loading, based on experimental data.

3) *Analysis Type:* A static structural analysis was executed to compute the Equivalent (Von Mises) Stress distribution across the specimen.

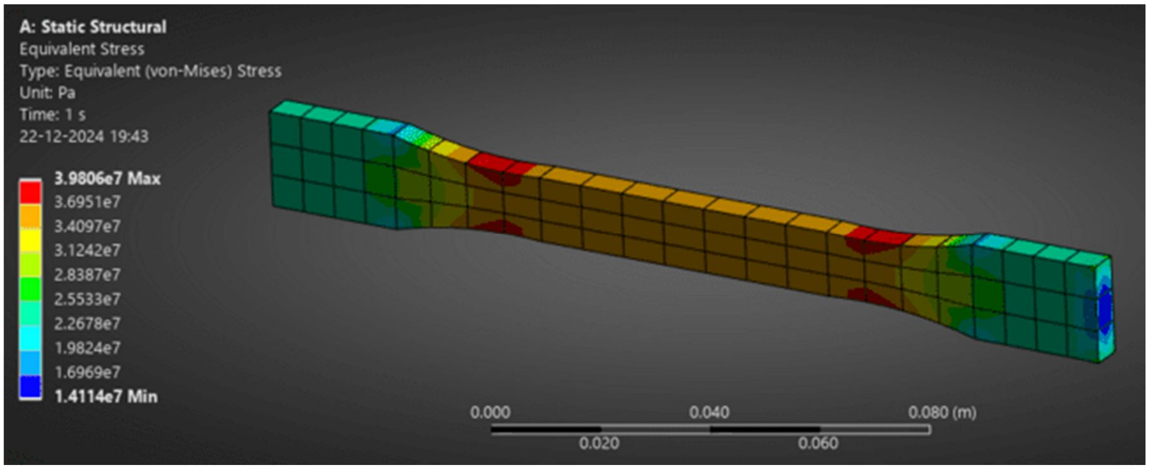

Fig. 17 Equivalent Stress (Von Mises) Distribution in the PLA Specimen

B. Results
- The highest stress concentration occurred at the fillet region—correlating strongly with the fracture location observed in physical testing.
- The Von Mises stress in the central gauge area was approximately **34 MPa**, confirming consistency between simulation and experimental failure behavior.
- The stress contours reflected a brittle failure mode, validating PLA's known material response and further supporting the reliability of the FEA model [8].

This confirms FEA as a valuable predictive tool for identifying critical stress regions and understanding the failure mechanics of 3D-printed polymer components.

VII. CONCLUSION

This study presented an integrated methodology for characterizing the tensile behaviour of 3D-printed PLA specimens by combining experimental testing, finite element analysis (FEA), and machine learning (ML). The synergy between physical validation, numerical simulation, and data-driven modelling offers a robust framework for mechanical analysis and performance prediction of additive-manufactured components.

The key outcomes of this work are summarized as follows:

1) Experimental Characterization: Three ASTM D638 Type I PLA specimens were printed using a Raise3D E2 and tested on an INSTRON 5582 UTM, yielding an average tensile strength of 32.35 MPa and modulus of 1308 MPa, confirming PLA’s brittle behaviour with elongation under 15%.
2) Fracture Analysis: Failure consistently occurred in the fillet region, identified as the zone of highest stress concentration. This was observed visually and further validated through simulation.
3) FEA Validation: ANSYS-based simulations accurately replicated the stress distribution observed during physical testing, with peak Von Mises stress (~34 MPa) localized at the fillet. This alignment between simulation and experimental outcomes demonstrates the predictive accuracy of FEA for stress localization in 3D-printed components.
4) Machine Learning Prediction: An Elastic Net Regression model trained on a publicly available Kaggle dataset achieved a prediction error of just 5.07%, effectively estimating tensile strength from print parameters. This demonstrates the potential of ML in optimizing print settings without exhaustive physical testing.

In conclusion, the combined use of physical experimentation, simulation, and ML offers a time-efficient and cost-effective approach for evaluating and improving the mechanical properties of 3D-printed PLA. The proposed methodology can be extended to other polymeric or composite materials, making it a scalable blueprint for hybrid experimental–computational–data-driven material characterization in additive manufacturing.

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