Predicting the Flexural & Hardness Properties of a 3D Printed specimen of different Polymer Materials using "ML&AI"

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Abstract

The current work is employing the application of ML/AI techniques to Predict the actual strength of 3D-printed parts of different polymer materials in comparison with experimental results. The test specimens are printed as per D780 ASTM standards mainly with arguably the most common FDM materials such as PLA, ABS, and PETG. Parameters relevant to printing of test specimen such as layer height, infill density, print direction, and temperature were adopted and 3D Printed specimen are tested for flexural and hardness properties which helps the ML models classify how different printing conditions affect the final mechanical strength.From the obtained results, it is observed that,flexural strength obtained in experimental test is 56.184MPa and for Maching learning models ANN predicted 43.657MPa,Random forest model predicted 49.483MPa and XGBoost model predicted 57.573MPa .and hardness in experimental test is 73N/mm2 and for Maching learning models ANN predicted 72.28N/mm2,Random forest model predicted 71.28N/mm2 and XGBoost model predicted 73.01N/mm2.

Finally it can be concluded that XGBoost model follows the experimental trend,for both flexural and hardness with accuracy of 98.53% and 97.25% hardness strength indicating superior predictive capability compared to ANN and Random Forest models.

Keywords

FDM 3D Printing, Machine Learning, Flexural and Hardness Properties, Predictive Modeling, Martials such as PLA,ABS and PETG

1. Introduction

Fused Deposition Modeling (FDM) has become one of the widely used techniques for 3D printing in recent years because of its inexpensive cost, simplicity, and ability to produce custom parts. The mechanical performance of the components printed with FDM can vary drastically with regard to printing conditions. Some of the factors that greatly influence the strength and durability of a printed part include the type of polymer used, layer height, infill density, print orientation, and printing temperature.

To better understand and predict these variations, this project focuses On developing a Machine learning (ML) and artificial intelligence (AI) based model that can estimate the Flexural strength and flexural modulus of 3D-printed specimens made from common Materials like PLA, ABS, and PETG. Standardized test specimens will be printed according To ASTM guidelines, and experimental tests such as Flexural testing and hardness testing will Be conducted to obtain Reliable mechanical data.

2. Motivation

3D printing has become part of modern manufacturing; however, the strength of printed parts varies considerably according to printing conditions. A slight change in layer height, infill, temperature, or orientation brings a significant effect on how strong or flexible a part becomes and thus interacts trial-and-error, wasting time and material. Hence, there is a need for a more intelligent and reliable method by which to understand and anticipate the mechanical performance of printed components before transcending into real production. This work aims at using real experimental testing coupled with machine learning to discover clear patterns around setting print conditions and flexural Behaviour. It does so to create good ML models that will be able to guide users to best parameters: reducing unnecessary prints and improving precision.

3.Objectives

Primary Objective

To develop a machine learning model that predicts the flexural properties of 3D-printed polymer parts.·Study the effect of printing parameters on the flexure behavior.

Specific Objectives

·Perform standard ASTM flexural testing and hardness testing for experimental data acquisition.

·Develop ML models to forecast flexural strength and modulus.

·Experimentally compare the outcomes versus the predicted results to validate.

·Optimize the 3D-printing parameters with ML insights.

·Reduce material wastage and time by lessening redundant tests.

4 Literature Review

- A.Kumar & Kruth (2017): Studied the influence of AM process parameters on mechanical properties of polymer composites.
- B.Domingo-Espin et al. (2015): Demonstrated ANN-based prediction of FDM mechanical properties.
- C.Dawoud et al. (2016): Compared mechanical behaviour of ABS fabricated using FDM and injection moulding.
- D.Shanmugam et al. (2020): Reviewed 3D-printed fiber-reinforced composites and flexural behaviour.
- E.Soleyman & Bazli (2021): Applied ML for predicting mechanical properties of 3D-printed parts

5.Working of the Project

The workflow includes:

1. Printing ASTM-standard specimens using PLA, ABS, PETG
2. Varying process parameters: layer height, infill %, temperature, orientation.

➢ **Table 1:** Varying process parameters: layer height, infill %, temperature, and orientation data's.

Parameter	PLA	ABS	PETG
Nozzle Temperature	190–220 °C	220–250 °C	220–250 °C
Bed Temperature	50–60 °C	90–110 °C	70–90 °C
Enclosure	Optional	Required	Optional
Cooling Fan	High (100%)	Minimal (0–20%)	Moderate (30–50%)
Bed Adhesion	Good adhesion to PEI or glue stick; minimal warping	ABS slurry recommended due to significant warping	Glue recommended due to excessive adhesion

3. Conducting flexural and hardness tests.
4. Preparing dataset → ML model training → testing → validation.

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6. Methodology

1. Material Selection: PLA, ABS, PETG.

2. Specimen Design: ASTM standard flexural samples.

Fig 1. Specimen samples

3. Testing: 3-point bending using UTM + hardness testing.

Fig 2 Flexural test in UTM

4. Data Pre Processing:clining,Normalization,Encoding.

5. Models Used:

   - Random Forest
   - XGBoost
   - ANN

6. Evaluation Matrics : MAE, RMSE, R^2, k-fold cross-validation.

Validation: Comparing predicted vs. Experimental flexureal results.

7. Flow chart

Fig 3. Flow chart

8. Hardware and Software Requriments

1. Hardware:

   - 3D Printer (PLA/ABS/PETG capable)
   - Computer (i5/i7, 16 GB RAM)
   - UTM (3-point bending fixture)

2. Software

   - 3D Printing Software: Cura, Slicer, Simplify3DML
   - Tools: Python,
   - Data Tools:

9.Outcomes

9.1Experimental results

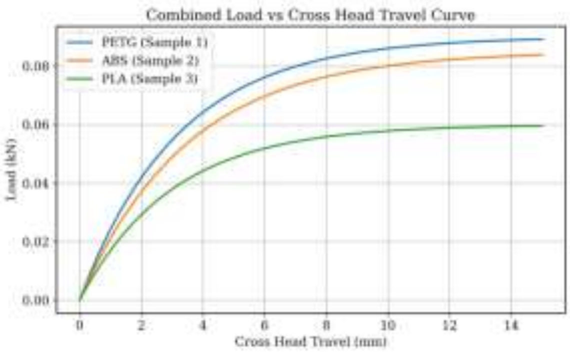

Fig 4 Interpretation of the Flexural Strength Graph

- Blue line represents – PETG (Sample 1)
  - ➢ Highest flexural strength (56.184 N/mm?)
  - ➢ Indicates superior resistance to bending induced failure
- Orange line represents – ABS (Sample 2)
  - ➢ Slightly lower but comparable flexural strength (54.733 N/mm)
  - ➢ Demonstrates balanced stiffness and Strength
- Green line represents – PLA (Sample 3)
  - ➢ Lowest flexural strength (37.245 N/mm2)
  - ➢ Confirms more brittle flexural behavior despite higher initial stiffness

Table 2 Experimental results output

Sample ID	Material	Dimensions (mm)	Test Type	Loading Rate	Flexural Strength (MPa)	Flexural Modulus (GPa)
1	PETG polymer	80 × 10 × 4	3-point flexural test	100 kN	56.184	0.056184
2	ABS polymer	80 × 10 × 4	3-point flexural test	100 kN	54.733	0.054733
3	PLA polymer	80 × 10 × 4	3-point flexural test	100 kN	37.245	0.037245

Table 3 Machine learning output of Flexural Strength (N/mm²)

Experimental Hardness Output

Table 8.2 Experimental results output

Material	Hardness (Experimental)
PLA	69
ABS	74
PETG	73

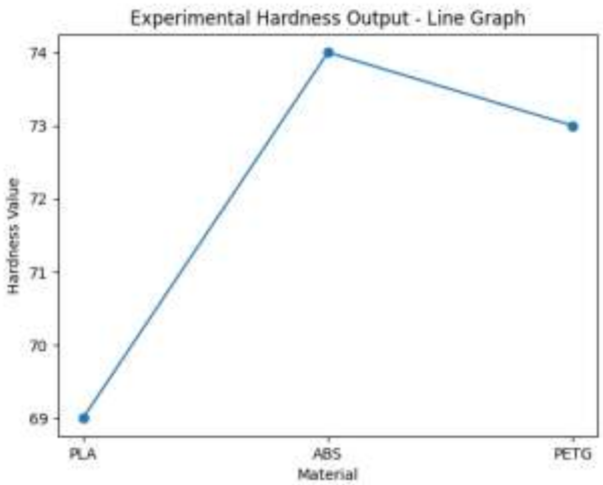

Fig.5 Experimental Hardness results output

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9.2 Machine Learning Prediction Results

Figure 6 shows the comparison between experimental and machine learning–predicted flexural strength for PLA, ABS, and PETG materials. The line graph illustrates that the XGBoost model closely follows the experimental trend, indicating superior predictive capability compared to ANN and Random Forest models.

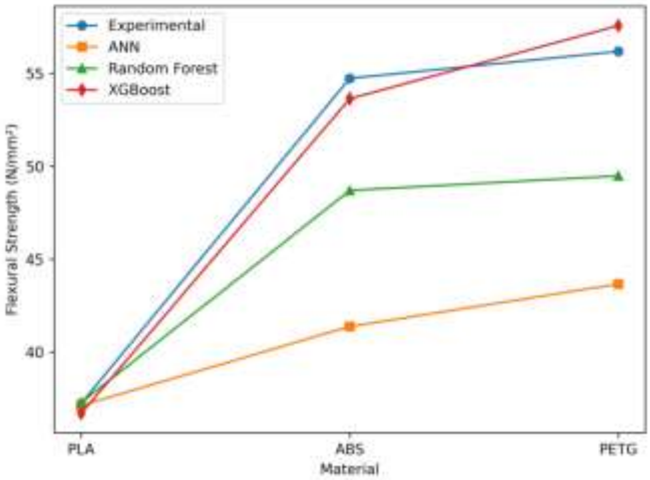

Fig.6 Comparison of experimental and ML-predicted flexural strength.

Table 4 Machine learning output of flexural

Material	Experimental (Actual)	ANN Predicted	Random Forest Predicted	XGBoost Predicted	XGBoost Accuracy
PLA	37.231	37.122	37.277	36.692	98.55%
ABS	54.733	41.374	48.700	53.638	98.00%
PETG	56.184	43.657	49.483	57.573	97.53%

Figure 7 presents the comparison of experimental and machine learning–predicted hardness values for PLA, ABS, and PETG. The results demonstrate strong agreement between experimental data and ML predictions, with XGBoost and Random Forest models exhibiting minimal deviation

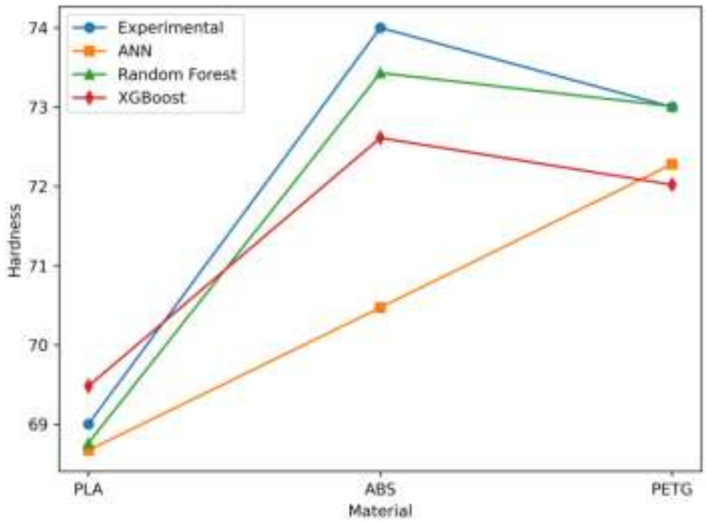

Fig 7 Comparison of experimental and ML-predicted hardness.

Table 5 Machine learning output of Hardness

Material	Experimental (Actual)	ANN Predicted	Random Forest Predicted	XGBoost Predicted	XGBoost Accuracy
PLA	69	68.67	68.76	69.48	99.30%
ABS	74	70.47	73.43	72.61	98.12%
PETG	73	72.28	73.01	72.02	98.66%

10. DISCUSSION

Random forest and xgboost models yielded high prediction accuracy. infill density, material type, and nozzle temperature were identified as key factors influencing flexural performance. more diverse datasets and additional parameters (post-processing, humidity) can further improve performance.

11. Conclusion

This study proves that ML/Al techniques can reliably predict the flexural properties of FDM-printed parts. The integration of experimental data with predictive modelling improves manufacturing efficiency, reduces trial-and-error, and supports smarter, data-driven decision-making in additive manufacturin.

12. References

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