Predicting Tensile Strength in 3D-Printed Materials Using Machine Learning

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Abstract

This project focuses on developing a machine learning-based predictive model for estimating the tensile strength of 3D-printed materials. Various factors such as layer height, infill density, nozzle temperature, and print speed influence the mechanical properties of printed materials. The study employs different regression algorithms, including Linear Regression, AdaBoost Regression, XGBoost Regression, Gradient Boosting Regression, and Random Forest Regression, to identify the best model for tensile strength prediction. The dataset used for training and evaluation consists of multiple print parameter combinations, and performance is assessed using mean square error and R-square value metrics. The results contribute to improving the optimization of 3D printing parameters for enhanced material performance.

1. **Introduction**

Three-dimensional (3D) printing has revolutionized manufacturing by enabling the creation of complex structures with high precision. However, predicting the mechanical properties of printed materials remains a challenge due to the multiple interacting process parameters. This study aims to develop a machine learning model that can accurately predict the tensile strength of 3D-printed parts based on printing parameters. The findings will help optimize printing settings to enhance product durability and efficiency.

2. Literature Survey

Several studies have explored the application of machine learning in optimizing 3D printing parameters:

- Delli & Chang (2018): Developed an automated process monitoring system for 3D printing using supervised machine learning to detect defects during the printing process.
- Jayasudha et al. (2022): Investigated different machine learning algorithms for predicting the tensile strength of 3D-printed parts, concluding that XGBoost outperformed other models.
- Tatar (2025): Explored the use of regression methods to predict 3D printing product quality, identifying Gaussian Process Regression (GPR) as the most accurate.
- Sharma et al. (2022): Studied the effect of fused deposition modeling (FDM) parameters on the dimensional variation of printed parts, utilizing decision trees for prediction.

3. Dataset Discussion

- The dataset used in this study contains printing parameters and their corresponding tensile strength values. Key parameters include:
- Layer Height: Determines the thickness of each deposited layer.
- Infill Density: Affects the internal structure and mechanical strength.
- Nozzle Temperature: Influences material melting and bonding.
- Print Speed: Impacts the accuracy and adhesion of layers.
- Wall Thickness: Affects overall structural integrity.

4. Approach and Methodology

The approach involves training multiple machine learning models and selecting the best-performing one:

1. Data Preprocessing: Normalization and handling missing values.
2. Feature Engineering: Identifying key parameters influencing tensile strength.
3. Model Selection: Training and evaluating different regression algorithms:
   - Linear Regression
   - AdaBoost Regression
   - XGBoost Regression
   - Gradient Boosting Regression
   - Random Forest Regression

4. **Performance Evaluation:** Comparing models based on mean square error (MSE) and R-square values.

Results: Random Forest Regression demonstrated the highest accuracy in predicting tensile strength, making it the preferred model for further optimization.

5. Future Work

Future research directions include:

- Enhancing feature engineering by incorporating additional material properties.
- Exploring deep learning models like neural networks for improved predictions.
- Developing a real-time predictive tool for industrial 3D printing applications.
- Extending the model to predict additional mechanical properties like elongation and impact resistance.

6. Conclusion

This study successfully developed a machine learning model to predict tensile strength in 3D-printed materials. By comparing multiple regression models, Random Forest Regression emerged as the most effective. The results highlight the potential of machine learning in optimizing 3D printing parameters for enhanced material performance, reducing trial-and-error experimentation, and improving production efficiency.

7. References

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