# Predicting Tensile Strength of 3D Printed Parts using Minimal Data

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**Abstract**

Mechanical engineers currently rely on their experience and trail-and-error to manage the trade-off between 3D printed material properties and print time when choosing 3D printing input parameters. This study shows the viability of low sample method for prediction of tensile strength of 3D printed parts using machine learning. This reduces the importance of experiential knowledge in using 3D printers and allow for reproducible customisation. A broad variety of supervised models were trained and evaluated on a dataset of 3D printing parameters and tension strength tensile testing results. We achieved an R2 value of 88.2%, an root mean squared error (RMSE) of 2.49, and mean absolute percentage error (MAPE) of 13.33 in predicting tensile strength given 3D print job configuration parameters using an ensemble stacking model comprised of our 3 best individual models. While not yet achieving our targets of 95%, 1.7, and 5.6 respectively, we believe the results are promising enough to warrant further research into applying this approach to 3D printing with tension strength constraints.

***Keywords—*** 3D-Printing, Data Generation, Low Sample Machine Learning, SMOTE, Tension Strength Prediction

# Contents

# 1 Introduction

## 1.1 Aims, Objectives and Goals

The aim of this project is to provide an easily reproducible, low sample method to predict tensile strength for a standard 3D printing setup. Therefore, the objectives of the project are to build and validate various machine learning models which predict tensile strength, using a small dataset which only uses standard input parameters that most 3D printers have. The objectives also include investigating methods which could boost the performance of this model, such as data generation.

As a result, the goal is a machine learning model that predicts tensile strength of a 3D printed part with the following performance criteria: $R^{2*} >= 0.95$, $RMSE^{\dagger} <= 1.7$, $MAPE^{\ddagger} <= 5.64$. It also required that the model do this using 25 or less experimentally gathered data samples per material. This model can be used to validate the hypothesis.

## 1.2 Background and Rationale

Mechanical engineers are faced with a trade-off between 3D printed material properties and print time when choosing 3D printing input parameters. Ideally, they want the fastest print time that still meets their required tensile strength specification, but currently rely on experience and trial and error to find this combination of input parameters. Therefore, a model which predicts tensile strength given the input parameters, will allow for engineers to find the optimum settings for their requirements without the need for trial and error.

Existing research that uses machine learning to optimise 3D printing processes has built similar models to optimise various mechanical properties (see Theoretical Framework section). These, however, use custom data acquisition setups and larger sample sizes, which are difficult to reproduce for the typical mechanical engineer. Therefore, the purpose of this project is to increase accessibility to optimised 3D printing setups, save time of mechanical engineers and increase print quality of 3D printing setups using this model.

# 2 Theoretical Framework

## 2.1 Literature

The use of machine learning to optimise aspects of 3D printing can be grouped into quality monitoring, 3D design generation and process or mechanical property optimisation. Goh et. al [1] provides a comprehensive review of these applications and their approaches. When considering process optimisation, machine learning has been used to optimise surface roughness [2][3], density [4][5], mechanical wear [6][7], tensile strength [8][9] and other properties [10][11]. This research uses datasets ranging in size from 70 samples to over 1000, with many using custom sensor and data acquisition setups. For comparison with this project, Bayraktar et. al [8] used a custom setup to collect 108 samples with 12 features, to predict the tensile strength of polylactic acid (PLA) plastic.

The majority of these works used simple, 3 layered neural network architectures to make their predictions, with a few prior works using random forests and support vector regression models. The literature shows very accurate predictions can be made using these architectures, but neural networks rely on larger datasets and may not be as effective with less data. The high accuracy achieved also suggests using a smaller dataset to make predictions is feasible. To allow for comparison, we have chosen the same error metrics as Bayraktar et. al [8].

$^*$ Coefficient of determination $^{\dagger}$ Root Mean Square Error $^{\ddagger}$ Mean Absolute Percentage Error

## 2.2 Theory

### 2.2.1 Evaluation Metrics

1. Mean absolute percentage error (MAPE) is a measure used for prediction accuracy. It is essentially the difference between the ground truth value and the predicted value all divided by the ground truth value. The result of this for every datapoint is averaged to get the MAPE.

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{1}$$

$$\tag{2}$$

2. The coefficient of determination or the $R^2$ value is a measure of how well the model matches up to the ground truth data. It can be thought of as a percentage of data points which are explained correctly by the model. It is the correlation coefficient squared and then converted into a percentage.

$$r^2 = \left(\frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{n\sum x^2 - (\sum x)^2)(n\sum y^2 - (\sum y)^2}}\right)^2 \cdot \frac{100}{1}\% \tag{3}$$

$$\tag{4}$$

3. Root mean square error (RMSE) is a measure of the difference between predicted and actual values. It is calculated by getting the average of all of the squared errors (predicted − actual). The square root of this is then calculated to get the RMSE. The RMSE is sensitive to outliers.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}{T}} \tag{5}$$

$$\tag{6}$$

### 2.2.2 Predictive Models

We will use random forests, support vector regression and linear regression. Support Vector Regression (SVR) is a machine learning model used for predicting continuous values. It uses the concept of finding the narrowest margin which all of the datapoints lie in, and makes use of the kernel trick.

Random forests are another variety of machine learning model which can be used for regression problems. They work by ensembling many decision trees and outputting the result which is the most common of the many trees predictions.

Linear regression is used to model a dependent variable where each independent variable contributes linearly to the result of the dependent variable.

#### 2.2.2.1 Principal Components Analysis

Principal Components Analysis (PCA) is an unsupervised statistical method for dimensionality reduction. By performing an eigenvalue decomposition, it allows you to find the eigenvectors which explain the majority of the variance in the data. These can then be used to visualise and represent the data in a low dimensional space.

#### 2.2.2.2 Data Generation Algorithms

We may also require the use of data generation algorithms to improve our performance. We have identified the synthetic minority oversampling technique (SMOTE) to be relevant for this.

The SMOTE algorithm is simpler. It generates samples by linearly interpolating existing samples, so as to create new, similar samples within existing the cluster in a high dimensional space. It is usually used to create more minority class samples, but can also be used to just create more data points.

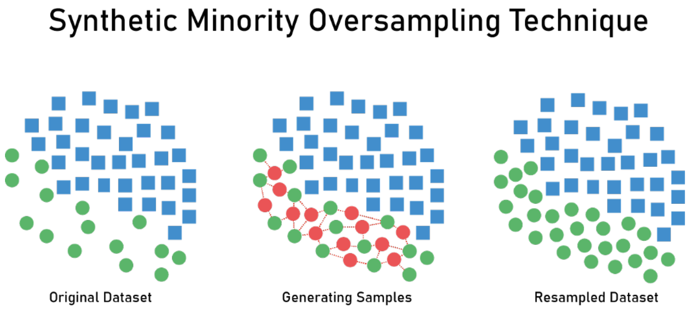



Figure 1: An intuitive explanation of SMOTE [12].

#### 2.2.2.3 Tensile Strength

The tensile strength of a material is the material's ability to withstand tensile stress ($\sigma$) per unit area. It is an important design parameter which is often used to determine mechanical lifespan and behaviours under more complicated loading scenarios.

$$\sigma = \frac{TensileForce}{CrossSectionalArea} \tag{7}$$

## 2.3 Research Question and Hypothesis

### 2.3.1 Research Question

The research question can be posed as follows: can we predict tensile strength of a 3D printed part accurately using less than 25 data gathered data samples per material, using only the input parameters of the printer? A list of the 9 input parameters can be found in the dataset description, in the Appendix.

### 2.3.2 Hypothesis

The hypothesis is that the tensile strength of a 3D printed part can be predicted with the performance criteria: $R^2 >= 0.95$, $RMSE <= 1.7$, $MAPE <= 5.64$, using 25 gathered data samples per material.

# 3 Method

## 3.1 Data Collection

We used an existing dataset made of two sets of 25 samples, where each set is for one printing material type (PLA and acrylonitrile butadiene styrene (ABS)). More information on this dataset can be found in the Appendix.

The procedure to collect such a dataset requires 3D printing standard tensile testing specimens with different input parameters and then experimentally measuring the resulting mechanical properties. For testing tensile strength, this is done by measuring the force required to pull the specimen apart and calculating the corresponding stress based on a known cross sectional area.

### 3.2 Data Analysis

The first step necessary was to gain an understanding the data set. Due to the size of the data-set it was possible to review the entire data-set to check that there were no malformed data-points or outliers which may have been collected in error.
As a quick way to assess if there was enough predictive capacity in the features to estimate the tension strength we conducted Principal Component Analysis on the data-set. We then analysed the relationship between the 3 largest principal components. It appeared that there was at least a weak correlation negative correlation with Principal Component 1 (PC 1) and a weak positive correlation with the second principal component (Figure 2). Plotting a 3D graph of PC 1 and PC 2 against tension strength gave us further hints that we could create a successful model as we could see that negative PC 1 and positive PC 2 predicted a higher tension strength (Figure 3a).

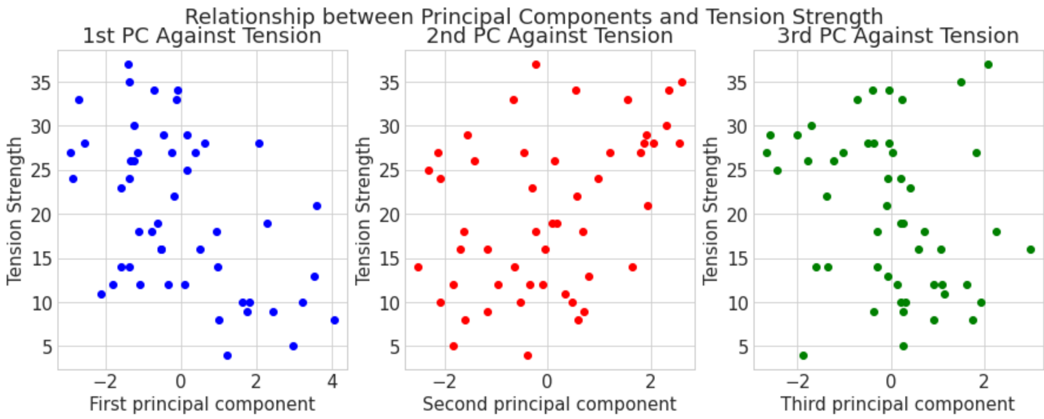
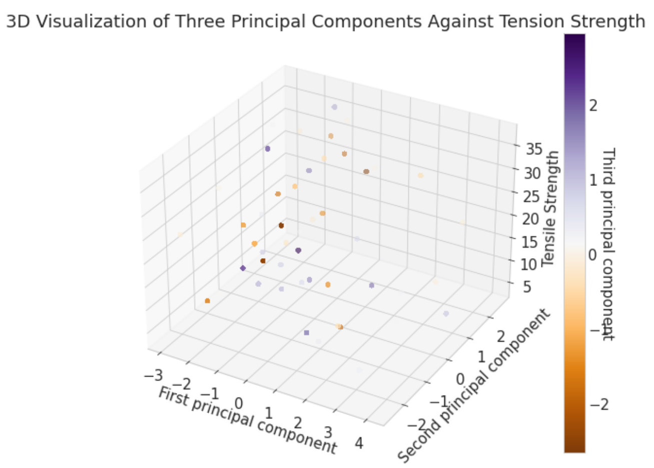
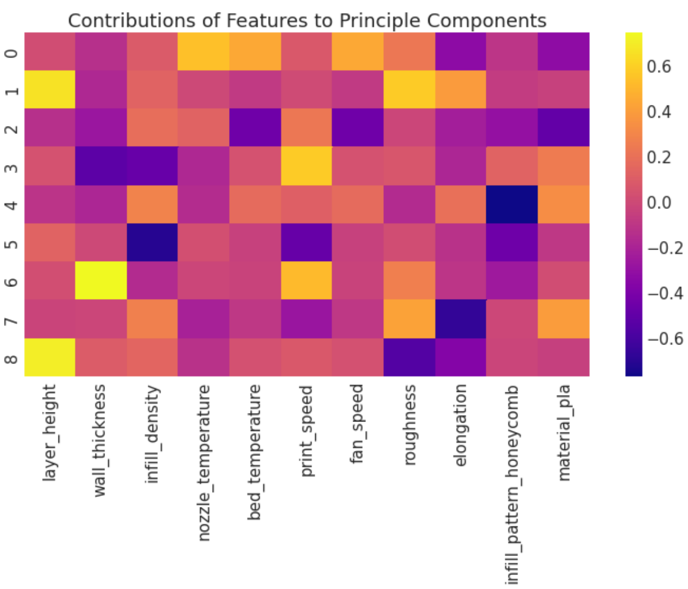



Figure 2: The First Three Principle Components Plotted Against Tension Strength

Next, to help understand the relationships between the features we examined the contributions of the features to the principle components. We confirmed some of our beliefs that *nozzle_temperature* and *base_temperature* were correlated as the both contribute with a high positive magnitude to the first PC (Figure 3b).




(a) 3D Plot of Three Principal Components Against Tensile Strength




(b) Grid Heatmap of the Contributions of the features to Principal Components

Figure 3: Further analysis of principle Components

We also saw that in order to explain all the variance in the dataset, 9 PCA components had to be used

(Figure 4). We deduced from this that all the input parameters of the 3D printer influenced the resulting tensile strength.

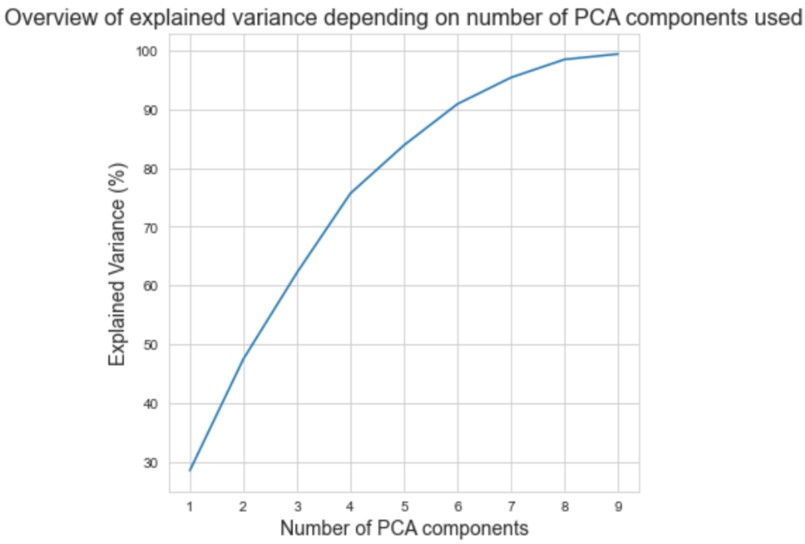



Figure 4: A plot of the explained variance as a function of the number of PCA components used.

## 3.3 Data Generation

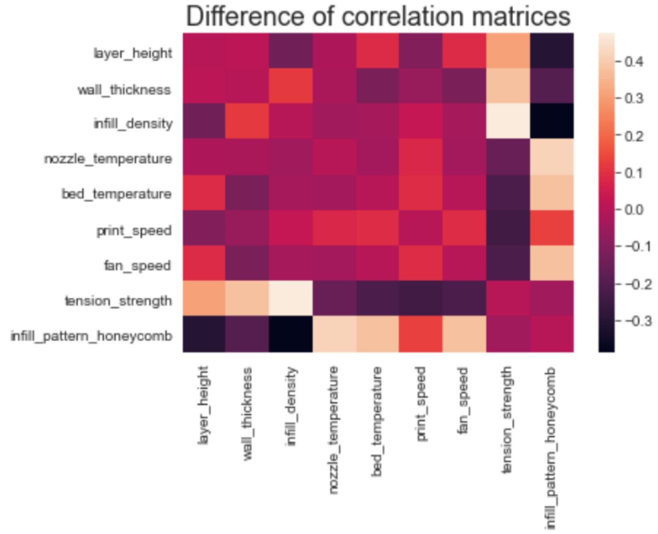
In order to increase the predictive performance of the models, we generated additional data samples to train on. We separated training and holdout test sets, and used the training set to generate new datapoints. These new points were then added to the training set and used to train models.

To evaluate the quality of the generated datapoints, we calculated the correlation matrix of the generated datapoints and the correlation matrix of the original training data. The difference of these correlation matrices was used to assess the quality of the generated data. The closer this matrix is to zero, the better the quality of the generated data.

### 3.3.1 SMOTE-NC

The SMOTE-NC algorithm is a variant of the SMOTE algorithm which handles categorical as well as numerical features. Figure 5a shows the quality of the generated data when different training and holdout test sets are used.


(a) Plot of maximum absolute correlation difference and the mean absolute correlation difference




(b) Difference correlation matrix between training data and generated data.

We used this as a basis to select a 70/30 train-test split, as this allows for high quality generated data but still enough test samples to meaningfully evaluate the models. We also saw that the SMOTE-NC algorithm was weaker at generating categorical features than numerical features, which can be seen by the generally higher values in Figure 5b for the categorical variable infill_pattern_honeycomb. Lastly, we generated different numbers of datapoints and found the more datapoints we generated, the poorer the overall quality of the generated data.

### 3.4 Modelling

To prepare the data for modelling, we one hot encoded the categorical features and normalised the dataset. For each model, we performed 5 fold cross validation and estimated the generalisation error via the holdout test set. Additionally, we experimented with boosting techniques such as Adaboost to improve performance.

## 4 Results and Analysis

### 4.1 Individual Models

Out of the individual models with no generated training data (Table 1) the Support vector Regression model performed best with an R2 of 66.2%. Next came the Kernel Ridge regression model with a R2 of 53.7%. It was clear that the Linear Regression Models performed worse than the kernel trick models (R2 of 26.5% for ridge regression and 0.35% for Lasso and 40.2% for Elastic Net Regression. The MLP model gave very poor results with a negative R2 which implies it totally failed to learn a model for the problem.
By using the extra data generated with SMOTE the kernel models improved substantially (Table 2) with R2 values of 77.6% for KRR and 86.3% SVR. Additionally we tested a Random Forest Model which gave an R2 value of 79.4%. The SVR model was the best performing individual model. The performance of the MLP model improved substantially with the extra generated data reaching a R2 of 58.3%.

### 4.2 Boosting

The results from Ada-boosting seemed to make the models over-fit on the training data and so had no real performance advantage for test data.

## 4.3 Ensemble Models

The ensemble models developed were only tested on the the data-set with additional generated data via SMOTE. The ensemble models gave the best results with a bagging model using simple average achieving 85.0%. A stacking of the best three individual models (SVR, KRR and RF) achieved the best results (Table 2) with an R2 of 88.2%.

Table 1: Summary of Test Results without Generated Data

| **Model Results** | | | |
|---|---|---|---|
| Model | MAPE | RMSE | R2 |
| **Target Performance** | 5.64 | 1.7 | 0.95 |
| **Linear Models** | | | |
| Ridge Regression | 37.455 | 6.220 | 0.265 |
| Lasso Regression | 31.600 | 5.849 | 0.350 |
| ElasticNet Regression | 30.647 | 5.610 | 0.402 |
| Multi-Layer Perceptron (MLP) | 120.006 | 154.983 | -0.00679 |
| **Kernel Trick Models** | | | |
| Kernel Ridge Regression (KRR) | 28.678 | 4.937 | 0.537 |
| Support Vector Regression (SVR) | 25.652 | 4.216 | 0.662 |
| **Ensemble Models** | | | |
| Adaboosted (SVR) | 27.595 | 4.672 | 0.585 |
| Bagging | 25.576 | 4.378 | 0.636 |
| Stacking (SVR+KRR+RF) | 24.684 | 4.694 | 0.581 |

Table 2: Summary of Test Results with SMOTE Generated Data

| **Model Results with SMOTE Generated Data** | | | |
|---|---|---|---|
| Model | MAPE | RMSE | R2 |
| **Target Performance** | 5.64 | 1.7 | 0.95 |
| **Linear Models** | | | |
| Ridge Regression | 42.522 | 6.838 | 0.112 |
| Lasso Regression | 42.514 | 6.837 | 0.112 |
| ElasticNet Regression | 33.860 | 6.157 | 0.280 |
| Multi-Layer Perceptron (MLP) | 17.967 | 4.688 | 0.583 |
| **Kernel Trick Models** | | | |
| Kernel Ridge Regression (KRR) | 16.457 | 3.434 | 0.776 |
| Random Forests (RF) Regressor | 16.115 | 3.296 | 0.794 |
| Support Vector Regression (SVR) | 14.651 | 2.686 | 0.863 |
| **Ensemble Models** | | | |
| Ada-boosted (SVR) | 39.994 | 8.074 | 0.196 |
| Bagging | 16.010 | 2.808 | 0.850 |
| Stacking (SVR+KRR+RF) | **13.330** | **2.490** | **0.882** |

# 5 Discussion

The results suggest that the most effective individual model is a support vector regression model (Table 2) and that stacking models is an effective method to increase performance for this prediction problem (Table 2). Additionally, our interim results support the notion that a low sample method for predicting tensile strength is feasible. Another interesting finding is the effectiveness of data generation techniques in improving prediction performance, based on the performance increase between Table 1 and Table 2. Lastly, the inability of the multilayer perceptron to learn from the dataset without generated datapoint may be due to this model being more complex and requiring more data to learn.

The best results show promise in being able to achieve the 95% $R^2$ score, the 1.7 RMSE and 5.64 MAPE values we set out to achieve, but requires further work. In particular, further work could focus on using generative adversarial networks to generate more and higher quality data, as this created a considerable improvement in performance. Further work could also quantify certainty of predictions, as this may be of interest to mechanical engineers using the model.

With respect to the literature, this paper showed that lower sample methods are a viable approach to modeling predictive aspects of the 3D printing process, but did not achieve results comparable to the state of the art as achieved by Bayrakter et. al [8].

# 6 Conclusion

This paper predicted the tensile strength of 3D printed parts with as few samples as possible. It sought to create a reproducible approach so that mechanical engineers may optimise their own 3D printing setup. It showed the viability and significant improvement in results by using a data generation technique, but was unable to achieve the state of the art performance as set out in the hypothesis. As a result, it suggested methods to achieve this performance as future work. This work limited itself to the use of two material types, PLA and ABS, and other materials with more complex behaviours may require more data or produce less convincing results.

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# A Appendix

## A.1 Dataset Information

The dataset is provided by the TR/Selcuk University Mechanical Engineering department. The dataset is available on Kaggle and is open to the public domain, under the Unlicense.

The data was collected to determine the effects of different input parameters on the two materials and were used to build a material classification model. The dataset involves 25 samples for each of the two materials, namely PLA and ABS, with a filament size of 2.85mm. The 3D printer used was an Ultimaker S5 3-D. To carry out tensile strength tests, a Sincotec GMBH tester capable of pulling 20 kN was used on standard ASTM A370 test specimens.

## A.2 Best Model Hyperparameters

Table 3: Best performing model with generated data as described.

| **Stacked Regressor Model Hyperparameters** | **SVR** | **KRR** | **Random Forest** |
|---|---|---|---|
| C | 70 | | |
| Gamma | 0.1 | 0.1 | |
| Alpha | | 0.2 | |
| Kernel | | Polynomial | |
| Max Tree Depth | | | 12 |
| Min Samples Split | | | 2 |