

Prediction of Surface Roughness of a Material in 3D Printing By Using Machine Learning Techniques

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Abstract

The surface roughness of 3D printed parts is an important factor that affects their appearance, performance, and durability. However, predicting the surface roughness of 3D printed parts accurately is challenging due to the complexity of the printing process and the influence of multiple factors. To improve the surface roughness of 3d printed parts, a data-driven predictive modeling is generated. that can predict the surface roughness of parts manufactured from plastic& ABS plastic(Acrylonitrile butadiene styrene) by means of Fused Deposition Modeling(FDM). Twelve input variables are defined (layer height, print speed, infill density, infill pattern, wall thickness, bed temperature, nozzle temperature, fan speed, material, roughness. Using a Roughness meter, the average value of surface roughness on each surface was obtained. From these experiment values , A machine learning model was trained and validated. The model with the best prediction results was the one generated by gradient boosting ,with a Mean Absolute Error (MAE)

1.Introduction

Three-dimensional (3D) printing, also known as additive manufacturing, has gained significant attention in various industries due to its ability to fabricate complex and customized objects. To achieving optimal surface quality in 3D-printed parts remains a challenge. Surface roughness plays a crucial role in determining the functional and aesthetic properties of the printed objects. The accurately predicting and controlling surface roughness is essential for ensuring high-quality prints and maximizing the performance of the final products. Traditional approaches to surface roughness prediction in 3D printing rely on empirical models based on experimental data. These models are often specific to particular materials, printing parameters, and geometries, limiting their applicability and accuracy. Additionally, they require extensive trial and error iterations, which can be time-consuming and costly.

Machine learning (ML) techniques have emerged as promising tools for surface roughness prediction in 3D printing. ML algorithms can leverage large datasets containing information on various printing parameters, material properties, and corresponding surface roughness measurements. By learning the complex relationships within this data, ML models can make accurate predictions of surface roughness for different printing conditions. The objective of this research is to develop an ML-based approach for predicting the surface roughness of materials in 3D printing. By training models on comprehensive datasets that capture a wide range of printing parameters, such as layer height, printing speed, infill density, and material characteristics, we aim to create models capable of accurately estimating the surface roughness of printed parts. Supervised learning techniques will be employed to train the ML models. The input parameters, including printing settings and material properties, will serve as



predictors, while the corresponding surface roughness values will be the target variables. Regression algorithms, such as random forest, support vector machines, or neural networks, will be utilized to capture the complex relationships between the input parameters and surface roughness outcomes.

To evaluate the performance of the ML models, various metrics, such as mean squared error, root mean squared error, and R-squared value, will be utilized. Cross-validation techniques will be employed to assess the generalization capabilities of the models and ensure their reliability in predicting surface roughness for new and unseen data points. The successful implementation of this research will offer significant benefits to the 3D printing industry. Accurate surface roughness prediction using ML

2. Literature review

prediction of surface roughness in 3D printing is a significant challenge in additive manufacturing. Surface roughness plays a crucial role in determining the quality, functionality, and aesthetics of printed parts. Achieving desired surface finish is important in various industries such as aerospace, automotive, and medical, where precise control over the surface quality is essential. Traditionally, surface roughness prediction in 3D printing has relied on empirical relationships derived from experimental observations. These relationships attempt to correlate process parameters (e.g., printing speed, layer height, temperature) with the resulting surface roughness. However, such empirical models often lack accuracy and generalizability, as they may not capture the complex interactions and non-linearities present in the additive manufacturing process.

In recent years, machine learning techniques have emerged as promising tools for predicting surface roughness in 3D printing. Machine learning leverages computational algorithms to automatically learn patterns and relationships within data, enabling accurate predictions and improved understanding of the underlying mechanisms. The utilization of machine learning

models will enable engineers and manufacturers to optimize the printing process, reduce material waste, and enhance the overall quality of printed objects. Additionally, the developed models can provide insights into the impact of different printing parameters on surface roughness, facilitating the design of new materials and printing strategies.

This research aims to utilize machine learning techniques to predict the surface roughness of materials in 3D printing. By surpassing the limitations of traditional empirical models, ML-based approaches offer the potential for more accurate and efficient predictions. Ultimately, this research contributes to advancing the field of 3D printing by improving surface quality control and enabling optimization of the printing process.

techniques for surface roughness prediction involves training models on a dataset that comprises process parameters and corresponding surface roughness measurements. By analyzing the data, the machine learning algorithms learn the intricate relationships between the process parameters and the resulting surface roughness. These models can then be used to make predictions on new sets of process parameters, facilitating optimization and control of the 3D printing process. Various machine learning algorithms have been explored for surface roughness prediction in 3D printing, including regression models, artificial neural networks, decision trees, support vector machines, and random forests. These algorithms offer different advantages and trade-offs in terms of prediction accuracy, model interpretability, and computational efficiency.

The application of machine learning in surface roughness prediction holds immense potential for advancing additive manufacturing. Accurate prediction of surface roughness can guide process parameter optimization, reduce trial-and-error experimentation, minimize material waste, and enhance the overall quality and consistency of 3D printed parts. In this literature survey, we aim to explore the existing research on the prediction of surface roughness in 3D printing using machine learning techniques. By



reviewing relevant studies, we seek to gain insights into the different approaches, algorithms, and factors that influence the accuracy and applicability of these prediction models. Through this survey, we hope to

2. Experimental Methods

Predicting the surface roughness of materials in 3D printing using machine learning can be approached as a regression problem, where the goal is to develop a model that can predict the roughness value based on input parameters or features. Here's a general outline of an experimental method that incorporates machine learning for this purpose.

- **Dataset collection:** Collect a dataset that includes samples of 3D printed objects along with corresponding surface roughness measurements. The dataset should cover a diverse range of material types, printing parameters, and geometries. It's important to ensure that the dataset is representative of the actual printing conditions and contains a sufficient number of samples for training and evaluation
- **Feature selection/extraction:** Identify the relevant input features that can potentially influence the surface roughness. These features can include printing parameters (e.g., layer height, print speed, nozzle temperature), material properties (e.g., viscosity, elasticity), and geometric characteristics (e.g., overhang angles, support structures). It's also possible to use image-based features extracted from the 3D printed object's surface, such as texture descriptors or height maps.
- **Data preprocessing:** Clean the dataset by handling missing values, outliers, and normalizing the features if necessary. Split the dataset into training, validation, and testing subsets.
- **Model training:** Choose an appropriate machine learning algorithm for

contribute to the understanding and advancement of machine learning-driven surface roughness prediction in additive manufacturing, paving the way for enhanced process control and quality assurance in 3D printing.

regression, such as linear regression, decision trees, random forests, or neural networks. Train the model using the training dataset, using the input features to predict the surface roughness values. During training, optimize the model's hyperparameters using techniques like cross-validation to ensure robustness and generalization.

- **Model evaluation:** Evaluate the trained model using the validation dataset to assess its performance. Metrics such as mean squared error (MSE) or mean absolute error (MAE) can be used to quantify the model's accuracy in predicting surface roughness. Adjust the model and its hyperparameters as needed based on the evaluation results.
- **Model deployment:** Once satisfied with the model's performance, apply it to predict the surface roughness of new, unseen 3D printed objects. Use the testing dataset to assess the model's predictive capability on unseen data and compare it with other methods or benchmarks if available.
- **Iteration and refinement:** As more data becomes available or new printing techniques are introduced, collect additional samples and repeat the process to improve the model's accuracy and adapt it to evolving printing conditions.

Remember that the success of this approach heavily depends on the quality and representativeness of the dataset, as well as the careful selection of input features and the choice of an appropriate machine learning algorithm. Additionally, it's essential to validate the model's predictions against physical measurements to ensure its reliability and usability in real-world scenarios.

Heatmap Using Correlation Matrix



Result

Mean Absolute Error

In machine learning, MAE is a model evaluation metric often used with regression models. For a worked example MAE calculation, do check my next article on Mean Absolute Error(MAE)-sample calculation

| MODEL | MEAN ABSOLUTE ERROR |
|-------------------|---------------------|
| Linear regression | 45.146517 |
| Decision tree | 50.933333 |
| Random forest | 44.514667 |
| Gradient boosting | 36.951636 |
| KNN | 144.60000 |

MEAN SQUARE ERROR

The mean square error between your expected and predicted values can be calculated using the mean squared error () function from the scikit-learn library.

The function takes a one dimensional array or list of the expected values and predicted values and returns the mean square error value.

| MODEL | MEAN SQUARE ERROR |
|-------------------|-------------------|
| Linear regression | 3186.846496 |
| Decision tree | 4673.733333 |
| Random forest | 2529.490427 |
| Gradient boosting | 2263.364051 |
| KNN | 28557.400000 |

Conclusion

- It was concluded that Gradient boosting algorithm is the best machine learning algorithm which is predicting the Surface roughness with minimum error.
- Lowest Mean absolute error is 36.95%(0.36)
- Lowest Mean squared error is 2263.3640
- Surface roughness prediction can help in optimizing manufacturing processes. By analyzing the relationship between process parameters and surface roughness, machine learning models can identify the optimal settings for achieving the desired surface finish.

This can lead to improved efficiency, reduced costs, and enhanced productivity.

- It was concluded that exploratory data analysis helped a lot to understand the data which is very much helpful in the selection of suitable machine learning model.
- Different statistical techniques help to find the feature or variable importance in this project.

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