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Prediction Of Surface Roughness Of Pla+ Material In Additive Manufacturing Using Machine Learning

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Abstract

This Project explores the prediction of surface roughness in Polylactic acid (PLA+) polymer material using Machine Learning (ML) and Additive Manufacturing (3D Printing). Key printing parameters like layer height, infill density, printing speed, nozzle temperature, and printing platform temperature are considered for improving surface morphology. Utilizing machine learning algorithms such as linear regression, support vector machine (SVM), XG-Boost, and random forest regressor, this Project employs Mini Tab Taguchi's Design of Experiment Method to compare model-fit accuracy. The focus is on five influential parameters—layer height, infill density, printing speed, and nozzle temperature using L25 orthogonal array sample datasets to enhance understanding and characterization of the material.

Key Words: Polylactic acid(PLA+), 3D Printing, Taguchi Method, Regression, Anova, Machine Learning- Google Colab

1. Introduction and Literature Review

This study leverages Machine Learning (ML) and Taguchi's Design of Experiments to optimize key parameters in 3D printing, aiming to enhance surface roughness in Polylactic acid (PLA+) materials. It seeks to improve the surface quality and deepen understanding of Additive Manufacturing.

The literature review highlights several approaches to optimizing 3D printing parameters for improved surface roughness and tensile strength in FDM PLA parts. Huang et al. [1] demonstrate the superiority of the APSO-KNN model over other classifiers, achieving a 100% TPR. Ahmed et al. [2] identify optimal conditions for tensile strength using Taguchi L18 analysis. Mohd Nazri Ahmad et al. [3] showcase Taguchi's method for minimal surface roughness with an L9 orthogonal array. K.-E.A. and J.K. et al. [4] emphasize the importance of high extraction temperatures for dimensional accuracy. A. E. Tontowi et al. [5] combine Taguchi and Response Surface Methodology for parameter optimization.

2. Materials And Methods

1. Material Selection: PLA+ (Enhanced PLA): For this study, PLA+ is the material of choice due to its superior properties over standard PLA. PLA+ offers increased strength, durability, and heat resistance, making it ideal for experimental work in 3D printing.

2. Taguchi Design of Experiments (DOE) Method:

The Taguchi DOE method is a statistical approach used to optimize processes and improve quality by systematically varying parameters and analyzing their effects. This method reduces the number of experiments needed by using orthogonal arrays, making it both efficient and cost-effective.

Table – 1: Taguchi values from Minitab software

SI. No	PS	NT	ID	LH	SR
1	50	200	20	0.1	2.833
2	50	210	25	0.12	3.922
3	50	215	30	0.14	4.825
4	50	220	35	0.16	5.885
5	50	225	40	0.18	5.1
6	60	200	25	0.14	6.408
7	60	210	30	0.16	5.606
8	60	215	35	0.18	4.536
9	60	220	40	0.1	5.421
10	60	225	20	0.12	4.202
11	70	200	30	0.18	4.788
12	70	210	35	0.1	5.263
13	70	215	40	0.12	4.717
14	70	220	20	0.14	5.321
15	70	225	25	0.16	5.347
16	80	200	35	0.12	4.523
17	80	210	40	0.14	4.732
18	80	215	20	0.16	4.985
19	80	220	25	0.18	4.673
20	80	225	30	0.1	5.051
21	90	200	40	0.16	5.692
22	90	210	20	0.18	4.897
23	90	215	25	0.1	4.606
24	90	220	30	0.12	5.427
25	90	225	35	0.14	5.351

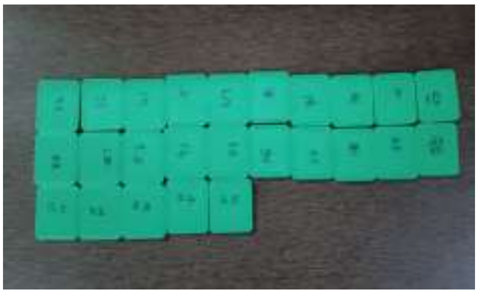

Figure 1. 3D printing parts

3. Additive Manufacturing (3D Printing):

Additive manufacturing, or 3D printing, creates three-dimensional objects from digital files by layering materials, using PLA+ filament for its enhanced properties. Figure 1 which represent the Additive manufacturing printed parts.

4. Surface Roughness Measurement:

Surface roughness, a key quality parameter of 3D-printed objects, is quantitatively measured using profilometers, with the Mitutoyo machine employed for this purpose.

5. Machine Learning: Machine learning involves the use of algorithms & statistical models to analyze and predict. Here is the Correlation Matrix for Which parameter mainly affects the output surface roughness values, which is shown in Figure 2. The Figure 3 showing the Metric Reprasentation which mean that what algorithm has a lower error than others.

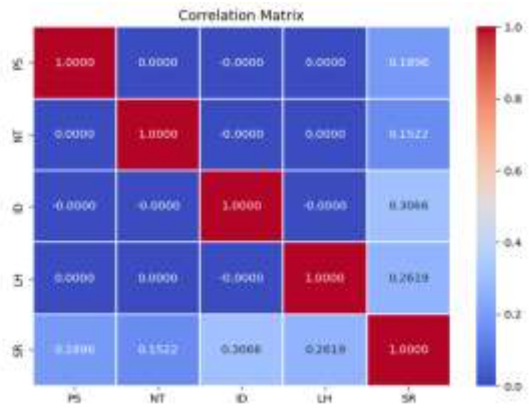

Figure 2. Correlation Matrix Chart

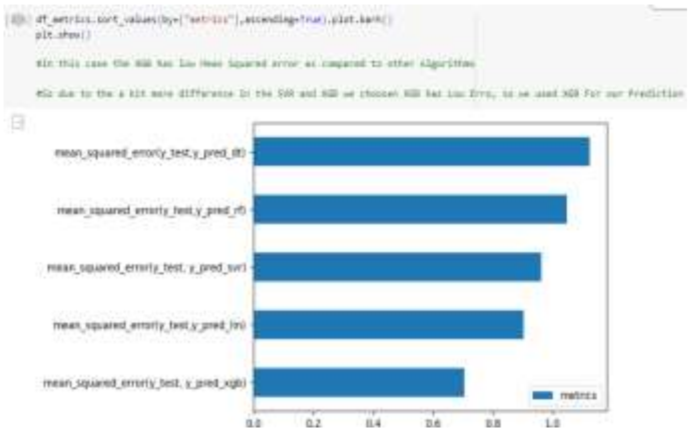

Figure 3. Metric Representation of Mean Squared Error

Statistical Method and Level of Significance: Statistical analysis using ANOVA identified significant factors and interactions with a significance level set at 0.05.

3. Results And Discussion:

Comparison of Taguchi values and ML values

1. If Taguchi values < Machine Learning values

   Project Success

2. If Taguchi values > Machine Learning values

   Project Fail

The above Figure 3. shows the Metric Representation of Mean Squared Erro. It shows that XG-Boost has fewer Errors as compared to other Algorithms.

Prediction in Machine Learning: The dataset provided encompassed various combinations of input parameters and corresponding surface roughness values obtained from both Taguchi and Machine Learning methods. Figure 4 which represent that used XG-Boost Algorithm for prediction of surface roughness in Machine Learning.

```
[216] value1=eval(input("Enter the value of Printing Speed:"))
      value2=eval(input("Enter the value of Nozel temperatue:"))
      value3=eval(input("Enter the value of Infilled Density:"))
      value4=eval(input("Enter the value of Layer Height:"))


      # Define a dictionary with input values
      new_data_dict = {'PS': value1, 'NT': value2, 'ID': value3, 'LH': value4}

      # Convert the dictionary to a DataFrame
      new_data = pd.DataFrame([new_data_dict])

      # Make predictions
      predicted_value = xgb_reg.predict(new_data)

      # Print the predicted value
      print("Predicted value:", predicted_value[0])

      Enter the value of Printing Speed:50
      Enter the value of Nozel temperatue:210
      Enter the value of Infilled Density:25
      Enter the value of Layer Height:0.12
      Predicted value: 3.9237566
```

Figure 4. Algorithm used for Prediction

4. Conclusion

Through the implementation of machine learning algorithms including linear regression, support vector machine (SVM), XG-Boost, and random forest regressor, alongside Mini Tab Taguchi's Design of Experiment Method, we compared model-fit accuracy. Our findings indicate that the XG Boost algorithm outperformed others and Taguchi values were found to be lower than predicted ML values which means that the project was correct. From XG-Boost Algorithm we can get accurate surface roughness values than other Machine Learning algorithms.

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