Section A-Research paper
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PREDICTION OF SURFACE ROUGHNESS IN ADDITIVELY MANUFACTURED SAMPLES IN PLA+ POLYMER MATERIAL THROUGH MACHINE LEARNING

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Abstract. Both artificial intelligence and additive manufacturing are excellent and revolutionary technologies. The main aim of this research paper is to predict surface roughness in additively manufactured processes in Poly Lactic Acid+ polymer material through different machine learning algorithms like support vector machine, linear regression, and two ensemble learning techniques Xtremegradient boosting and randomforest regressor. All machine learning is trained and tested. Predictive model of surface roughness is developed and machine learning behaviour is analyzed. Taguchi's Design of the Experiment was used to make L25 orthogonal array sample datasets. The machine model works on five parameters that influence layer geometries: layer height, infill density, printing speed, and nozzle temperature with a 0-degree raster angle. By applying all machine learning algorithms, random forest regression is best model, which gives 94.85% accurate results in datasets with minimum mean squared error of approximate 0.1255 and maximum r2 score of approximate. 0.9685.

Keywords: Additive Manufacturing, Poly lactic acid (PLA+) material, fused deposition modelling, Machine learning.

1. Introduction

According to recent studies, the implementation of machine learning (ML) methods may provide both improved speculate performance and increased productivity in the industrial sector. Additive manufacturing (AM) is an auspicious technology to manufactured components with intricate geometries. It can produce complex parts with minimum price and take time and without using special tooling system like molds compared to traditional manufacturing technologies.

Nomenclature			
ML	Machine learning	AM	Additive manufacturing
FDM	Fused deposition modelling	3D	Three-dimensional
PLA	Poly lactic acid	RMSE	Root mean square Error
Ra	Surface roughness (μm)	DoE	Design of experiments
ASTM	American Society for Testing and Materials	AI	Artificial intelligence
FFF	Fused filament fabrication	ABS	Acrylonitrile butadiene styrene
CAD	Computer-aided design	MSE	Mean Squared Error

Additive manufacturing, also referred to as AM, is the method of joining the material (layer-by-layer deposition) with the help of 3D models. In comparison with subtractive manufacturing techniques, AM is defined by the ASTM as "a process of incorporating materials to create 3D objects from 3D model data, generally layer upon layer deposition [1]. FDM is “a material extrusion process that is used to make polymer material parts by the heating of material filaments and the deposition of material layer by layer and make 3d objects” [2].

The roughness of a surface plays a significant role in machining processes because it has a direct impact on the functional specifications of the machined parts. [3], [4]. According to a survey, FDM is the most frequently utilized AM technology at the present time. One of the main areas of focus for enhancing FDM part quality has been the development of predictive models that link process factors (i.e., machine settings) and material qualities with the printed part properties [5]. Shaha et al [6], the DoE method was used to examine the impact of machine parameters on printed component surface roughness. The researcher determined that layer height was a significant determinant, but that there was no significant relationship between surface roughness and nozzle temperature. The investigation detailed in reference number [7] demonstrates how different machine configurations affect surface roughness. It was discovered that the height of the slice and the width of the raster have an impact on surface roughness. Meanwhile, P.K. Rao et al. [8], [9] conducted experiments to determine the machine settings that result in the

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smoothest surface finish, which is associated with high temperatures, thin layers, and a high feed/flow rate ratio. Similarly, R. Anitha et al. [9] reports on similar research where the thickness of the deposited filament, layer height, and extrusion speed were found to affect surface roughness. Popescu et al.[10] discussed that due to the various types of 3D printers, materials, and slicing software available, experimental methods may not be able to produce consistent results that accurately reflect the material's behavior in reality. To address this issue, theoretical modeling and finite element analysis were used to connect the mechanical properties of 3D-printed samples with material and process parameters[11]. However, the complex microstructure of 3D-printed parts, such as irregular pores and surface interactions, make it difficult to accurately model and simulate. Therefore, the accuracy and reliability of these methods are uncertain. To overcome these challenges, ML techniques, as a form of AI, can learn patterns between input features and output results automatically based on training data, without explicit programming [12]. In the context of the ME-AM process, the use of ML may provide effective solutions to the aforementioned issues [13]. The quality of parts produced by FFF can be impacted by variations in the thermal influence between layers during the layer-by-layer material deposition process. Such variations can cause issues like surface roughness, microstructural defects, and poor mechanical properties [14]. To address this, Boschetto et al.[15] developed a predictive modeling strategy to evaluate the surface roughness of FFF-printed items, and this strategy was demonstrated through a series of experiments. Boschetto and Bottini [16] also developed a model that can predict surface roughness of FFF-printed parts that underwent barrel finishing. Reeves and Cobb [17] created an analytical model that examined the effects of layer thickness, surface angle, layer profile angle, and layer composition on the surface roughness of stereolithography-printed parts. Meanwhile, Ahn et al. [18] developed a technique for predicting the surface roughness of 3D-printed parts using geometric data from an STL file. They fabricated multiple specimens on an SLA 3500 machine and measured their surface roughness with a profilometer.

Mishra and colleagues [19], [20] conducted experiments to examine how six different process parameters affect the mechanical strength of parts produced by FDM). The parameters included air gap, part orientation, layer thickness, raster angle, contour number, and raster width. The significance of each process parameter was determined using an analysis of variance. The study's findings revealed that air gap, contour number, and part orientation had the most substantial impact on the parts' strength. Bharat and colleagues [21] examined how various process parameters, such as layer thickness, air gap, road width, build orientation, and model temperature, affect the surface finish of FDM-built parts. The study employed a fractional factorial design with two levels for each factor. The results indicated that part orientation and layer height had the main impact on surface quality, with a part orientation of 70° and layer thickness of 0.007" yielding the best surface finish. Model temperature, air gap, and road width had minimal effect on the surface finish of FDM parts. In a similar study, Garg et al. [22] investigated the effects of part orientation on the dimensional accuracy and surface finish of FDM ABS P430 parts at seven different angles (0°, 15°, 30°, 45°, 60°, 75°, and 90° about the Y-axis). They found that part orientation had a considerable influence on both dimensional accuracy and surface finish, with the most desirable outcomes obtained at a 45° angle. The impact of model temperature, layer thickness, and part fill style on the surface roughness of FDM-built parts was studied by Daniel Horvath et al. [23]. All factors were found to have a significant effect on surface roughness, with layer thickness having the greatest impact. Reducing the layer thickness resulted in decreased roughness. Peârez et al. [24] also investigated surface roughness and dimensional accuracy in ABS P400 parts, creating four prototypes with different slope variations. Past studies have primarily concentrated on creating different methods for estimating surface roughness in AM processes. However, there has been minimal research on predicting surface roughness in AM utilizing heterogeneous sensors and data-driven techniques. To fill this void in research, a new data-driven predictive modeling technique fitted in machine learning has been introduced to predict the surface roughness of AM components using FFF.

2.1. Overview of Fused Deposition Modelling

FDM is a 3D printing technology that works by extruding a thin strand of molten material, typically thermoplastic, through a heated nozzle. The nozzle is mounted on a movable arm, which moves in the X, Y, and Z directions according to the design specifications of the 3D model [25]. The material is deposited layer by layer, with each layer fusing to the previous one to create a solid object. The FDM process with the components (see Fig 1)

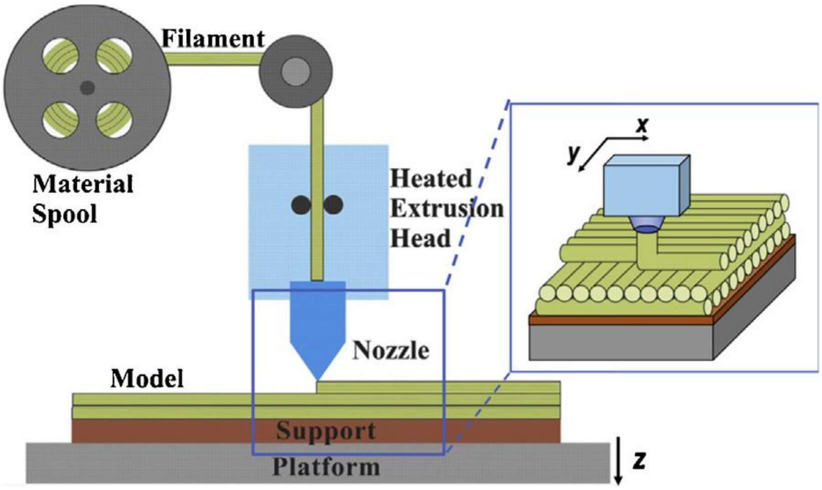

Fig. 1. FDM procedures of the 3D printing [25].

The process starts with the design of a 3D model using CAD software. The 3d model design is then convert into a format that can be read by the 3D printer, typically an STL file. The 3D printer software then analyzes the design and creates a toolpath, which is a set of instructions that tell the printer where and how to deposit the material to create the object.
The material used in FDM is typically a filament, which is a long, thin strand of thermoplastic material, such as ABS or PLA. The filament is fed into the printer through a spool and is heated to a melting point. The melted material is then extruded through the nozzle in a controlled manner, forming the object layer by layer. During the printing process, the object is supported by a platform, which can be either fixed or movable, depending on the printer design. As each layer is deposited, the platform is lowered or moved, allowing the next layer to be added. FDM 3D printers can produce objects with a high level of detail and accuracy, making them useful for a variety of applications, from rapid prototyping to producing end-use parts.

3. Experimental work

3.1 Material

PLA and PLA+ are two types of 3D printing filaments that are widely used. PLA is a biodegradable and environmentally friendly material that is typically derived from corn starch or sugarcane. On the other hand, PLA+ is an advanced version of PLA that boasts enhanced physical properties like increased strength, durability, and heat resistance. Numakers Company procures the PLA+ material for all experimental work.

PLA is crafted from natural and renewable resources such as sugarcane or cornstarch. To enhance its strength and durability, PLA+ is created by adding substances like carbon fiber, metal particles, or other polymers. The result is a stronger and more durable material that can withstand higher stresses without breaking or cracking. PLA+ is particularly useful for printing objects that require more strength, durability, and resilience, and it retains its shape and physical properties even at temperatures up to 90 degrees Celsius. Its improved adhesion properties make it less prone to warping and ideal for printing large objects. Additionally, PLA+ has best layer sticking and less shrinkage with less warpage than PLA, which change to a printed object that is closer to the same size and shape, with less warping or distortion during the 3D printing. Finally, PLA+ has a matte finish due to the natural additives in the material [26]–[28].Both PLA and PLA+ are great options for 3D printing. PLA is suitable for general-purpose printing, whereas PLA+ is more appropriate for printing objects that require greater strength, durability, and resistance to heat. PLA+ has enhanced properties compared to PLA, such as improved strength, durability, and heat resistance, making it the preferred material for printing high-performance objects. However, it is slightly more difficult to print with than PLA, and it is also more expensive due to the added additives. PLA+ is a thermoplastic polymer that is commonly utilized in fused deposition modeling. It is an eco-friendly material that is fully biodegradable and produced from renewable resources obtained from corn starch fermentation. Additionally, it is cost-effective and offered in a range of colors. [29], [30] provides information on the properties of PLA. In FDM, the print quality can be impacted by several process parameters, including layer thickness, nozzle temperature, ,print speed, infill density, print orientation, shell thickness, and printing pattern. Only the parameters that directly affect surface roughness and mechanical properties are considered, which includes layer thickness, infill density, and nozzle temperature. These parameters, along with their corresponding levels for an FDM 3D printer with a 0.4 mm nozzle diameter, are chosen using trial-and-error models. Table 1 presents the selected process parameters.

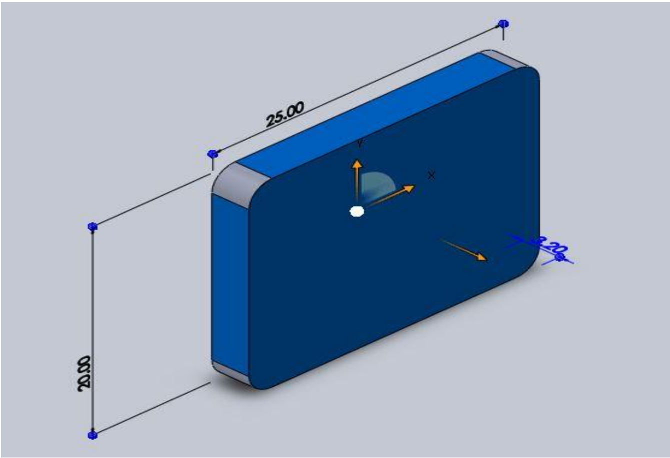

Fig 2. Schematic Diagram of 3D sample parts with Geometry 25x20x3.2 mm³.

The experiment keeps all other parameters at a constant value while focusing on layer thickness, infill density, and nozzle temperature as the main process parameters. The printing speed, traveling speed, printing pattern, and shell thickness are also set to predetermined values. No supports are needed for printing the CAD models, so they are disabled. An orthogonal array (OA) is generated using MINITAB L25 software, which uses a 5-level Taguchi design with 5 factors. The L25 design is selected, resulting in a 5x5 array presented in Table 1. The specimens developed in a SolidWorks CAD model have dimensions of 25*20*3.2 mm³. (see in fig 2)

3.2 Taguchi Method

Genichi Taguchi developed the Taguchi method, which aims to reduce process variation through a robust design of experiment and produce very high-quality products at a low cost for manufacturers. The method involves using a taguchi orthogonal array to organize the parameters that affect the process and the dimensions at which they are varied. The Taguchi method differs from the factorial design in that it only tests pairs of combinations, rather than all possible combinations. This approach is useful for identifying which factors have an impact on product quality while minimizing the amount of experimentation required, thereby saving time and resources. The proposed experimental design by Taguchi is discussed in reference [31].

The Taguchi Orthogonal Array (OA) design is a fractional-factorial model that ensures all levels and factors are equally considered. This allows for independent evaluation of factors, despite the functionality of the design. The Taguchi orthogonal array design L25 chosen in Table 1 shows the orthogonal array selected for the parameters and levels.

Table1: Control factors and different levels used for the Experiments

Parameters	L1	L2	L3	L4	L5
Printing Speed	50	60	70	80	90
Nozzle Temperature	200	207.5	215	222.5	230
Infill Density %	35	40	45	50	55
Layer Height	0.12	0.14	0.16	0.18	0.20

3.3 Fabrication and experimental setup

A total of 25 samples were printed according to the Taguchi L25 orthogonal array, as illustrated in Figure 4. These samples were printed using an Ender 3 3D printer, which is see in Figure 3. The specifications of this 3D printer are provided in Table 2. To test the surface roughness of the PLA+ material printed part, the Taylor Hobson surface roughness tester equipment was used. The components that were fabricated underwent testing using the Taylor Hobson machine shown in Figure 5, which has a range of approximately 0.05 to 12.25 um and is used in battery connectivity operations. Before testing the fabricated parts, it was necessary to check whether the diamond tip connected to the stylus was straight or not. Additionally, the surface roughness of the given sample base plate, which measured 6 um, was examined. Surface roughness was tested in three different positions of the sample parts, and the average of all three positions was taken to determine the final surface roughness (Avg), as shown in Table 3.

Section A-Research paper
ISSN 2063-5346

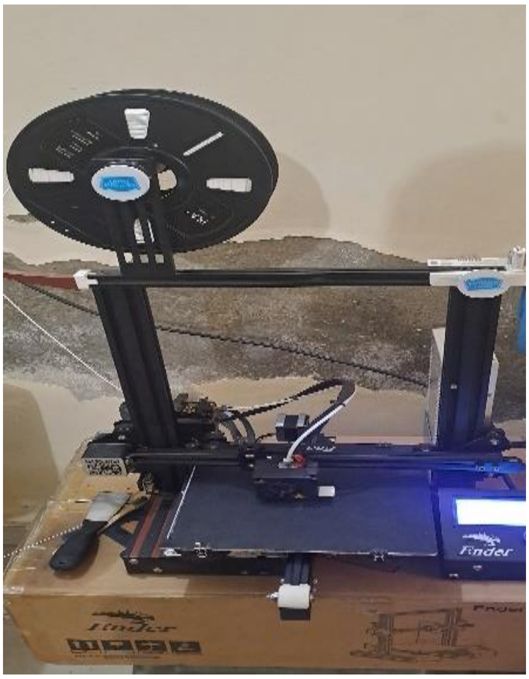

Fig 3. Ender-3 3D printer machine

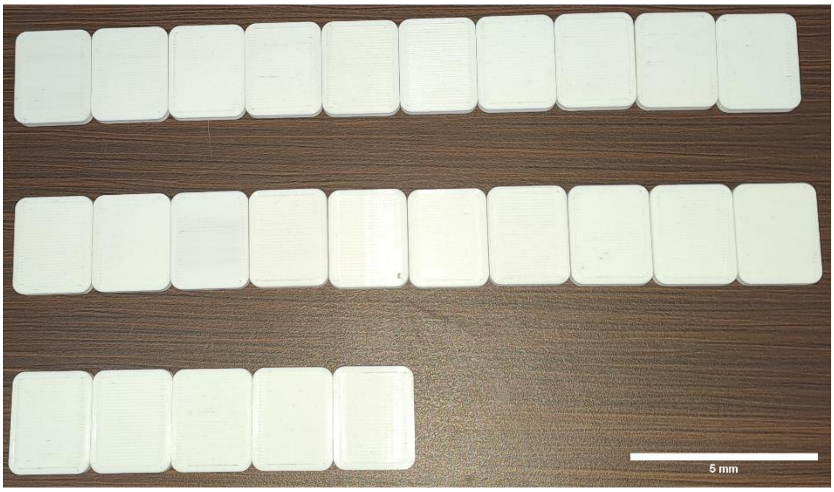

Fig 4. 3d Printed sample parts

Fig 5. Taylor Hobson surface roughness tester with printed sample parts

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Table 2: Specification of Ender-3 3D printer.

S.No.	Parameter	Type/Size
1	Bed size	235 * 235
2	Bed type	Heated
3	Max travel	X= 235, Y = 235. Z = 250
4	Nozzle size	0.4 mm
5	File supported	G code
6	Material Supported	PLA, PLA+, ABS
7	Display size	2.5 Inch
8	Max speed	120 mm/s
9	Power supply	220 – volt AC, 240Watt

Table 3: Experimental Result of surface roughness in different Parameters
Taguchi L25 orthogonal array.

Exp No.	Printing Speed	Nozzle Temperature	Infill Density	Layer height	SR (Ra1)	SR (Ra2)	SR (Ra2)	SR Average
1	50	200	35	0.12	4.24	4.3	4.08	4.20
2	50	207.5	40	0.14	5.72	5.86	5.25	5.61
3	50	215	45	0.16	6.50	6.31	6.21	6.34
4	50	222.5	50	0.18	7.21	7.88	7.46	7.51
5	50	230	55	0.2	9.54	9.36	8.94	9.28
6	60	200	40	0.16	6.44	7.1	6.32	6.62
7	60	207.5	45	0.18	7.31	7.84	8.44	7.86
8	60	215	50	0.2	8.41	8.19	8.75	8.45
9	60	222.5	55	0.12	4.12	4.365	4.62	4.4
10	60	230	35	0.14	5.84	5.7	5.81	5.78
11	70	200	45	0.2	8.89	9.12	9.4	9.13
12	70	207.5	50	0.12	4.14	4.68	4.84	4.55
13	70	215	55	0.14	5.94	5.34	6.24	5.84
14	70	222.5	35	0.16	6.34	6.84	6.94	6.70
15	70	230	40	0.18	8.154	8.54	8.21	8.30
16	80	200	50	0.14	6.25	6.32	6.05	6.20
17	80	207.5	55	0.16	7.45	7.64	6.84	7.31
18	80	215	35	0.18	8.54	8.89	8.24	8.55
19	80	222.5	40	0.2	7.55	7.3	7.95	7.6
20	80	230	45	0.12	5.15	5.89	5.25	5.43
21	90	200	55	0.18	9.32	9.75	8.95	9.34
22	90	207.5	35	0.2	10.25	9.98	9.84	10.02
23	90	215	40	0.12	7.1	6.84	6.35	6.76
24	90	222.5	45	0.14	6.65	6.9	6.25	6.6
25	90	230	50	0.16	8.21	8.75	8.1	8.35

3. Result and discussion

The generated machine learning model considers a total of four input parameters, with surface roughness measurement serving as the output. The input data or features consist of the following printing parameters: printing speed, Infill Pattern (IP), nozzle temperature, and Layer Thickness (LT), with a raster angle of 0 degrees. These parameters were obtained through the experimental procedure outlined in the experimental work, which was then used to calculate the surface roughness output of the 3D printed sample parts. Figure 6 displays the correlation between the input and output variables of the experimental datasets, while Figure 7 shows the Heatmap correlation created using Python programming.

3.1 Effect of printing parameter in surface roughness

Layer height. Printing speed, nozzle temperature and Infill density all the four parameters shown different impact on the surface roughness which is shown in the figure 6.

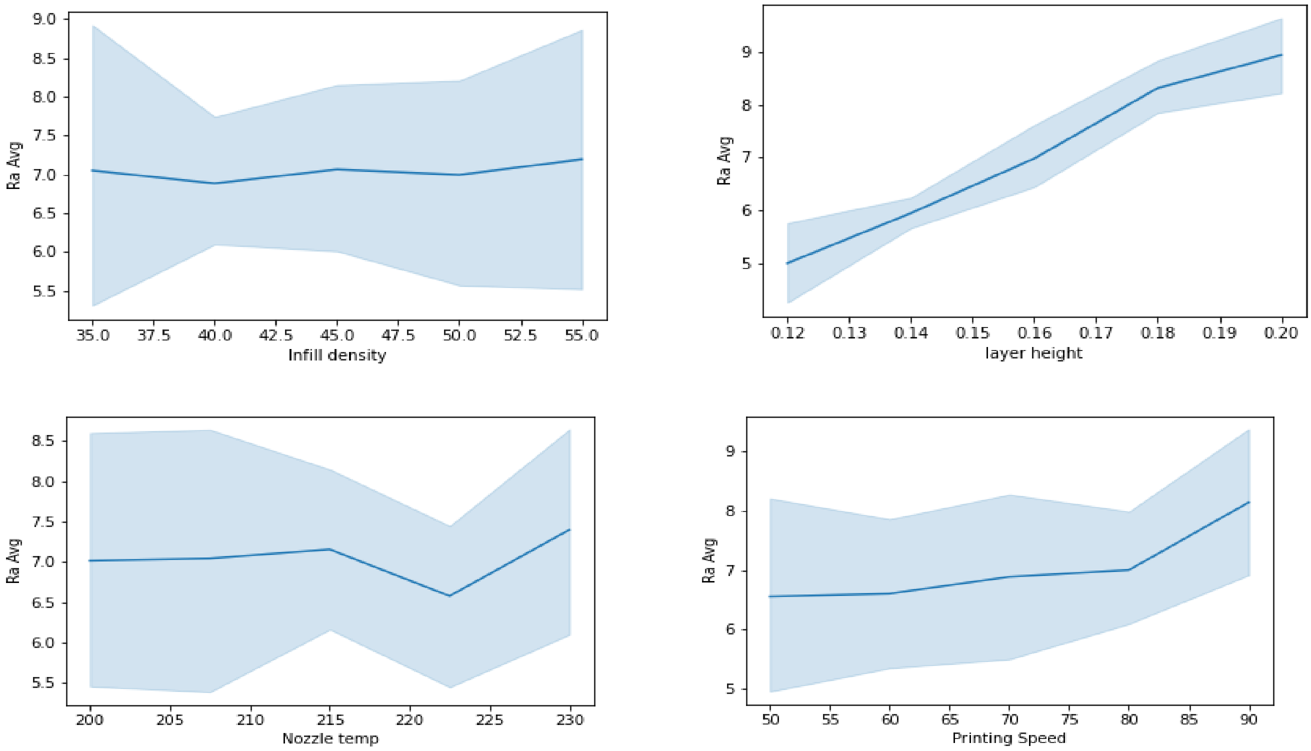

Fig. 6. show variation of different parameters with surface roughness (Ra)

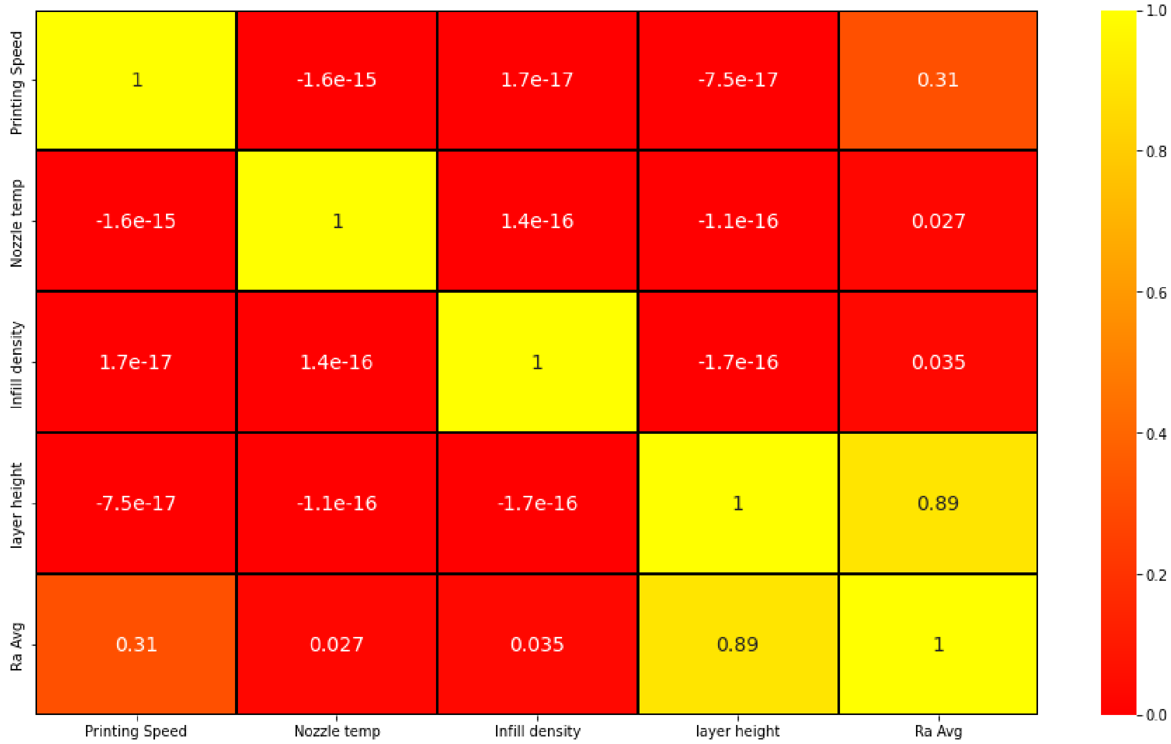

Fig. 7. Heatmap of correlation with surface roughness with other parameters

This heatmap gives the percentage of correlation of input features to the output features(Surface Roughness). This heatmap gives the correlation in percentage which is given below

1. Printing speed is 31% corr. With Ra
2. Nozzle temperature is 2.7% corr. with Ra
3. Infill density is 3.5% corr. with Ra
4. Layer height is 89% corr. With Ra

The correlation analysis reveals that layer height has a very strong correlation with surface roughness, at approximately 89%. Conversely, infill density and nozzle temperature have the least correlation with surface roughness. Infill density primarily affects tensile strength rather than surface roughness, as it fills the inside of the material in 3D printed parts. Nozzle temperature also has minimal correlation, as the melting temperature of the PLA+ polymer used in the experiment is around 200-230 degrees Celsius, as indicated on the filament coils purchased from the Numkers company. Given these findings, we eliminated the two least correlated parameters, nozzle temperature and infill density, and focused on the highly correlated layer height parameter. The dataset was then split into training and testing sets, with 75% allocated for training and 25% for testing. The machine learning model was applied to the datasets.

3.2 ML modelling

The specimens were manufactured with FDM 3D printing and tested for surface roughness on a Taylor Hobson surface roughness tester. Different machine learning is used to predict the surface roughness of the 3D printed parts, which show different results in the training and testing datasets . Working procedure of the ML is shown by the flow chart in the figure 8.

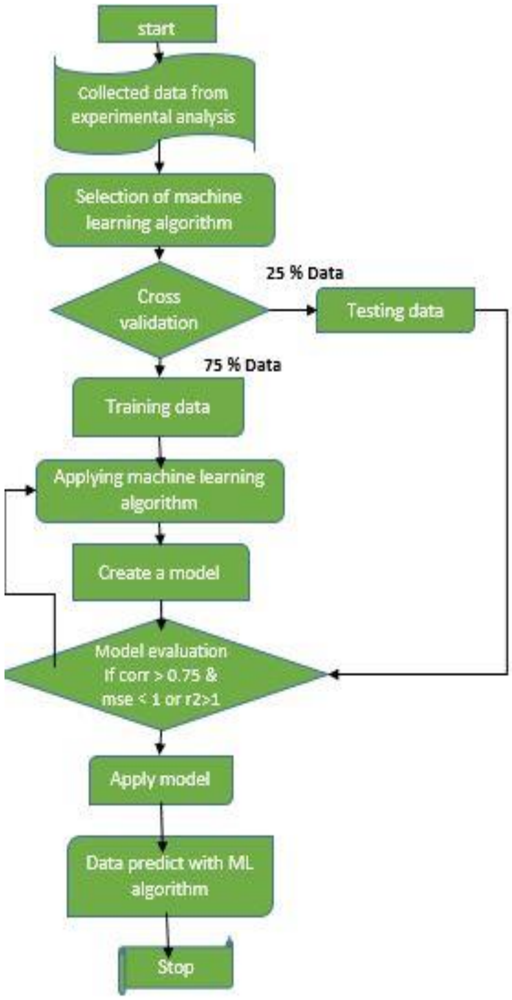

Fig 8. Working procedure of different ML created by flow chart

Table 5. Training and testing result in different Ml algorithm

Machine Learning algorithm	Training score (%)	Testing score
Linear regression	85.0	84.29

Support vector machine	3.08	-3.099
Random forest repressor	94.45	95.45
Gradient Boosting regression	98.871	36.67

Random forest regression shows a better-fitted algorithm on training and testing datasets, which is shown in the above table 5 all over the machine learning I am also checking the evaluation of all 4 algorithms. To determine whether a machine learning regression model is good or not, you can use various evaluation metrics, such as MSE: which measures the average squared difference between the predicted and actual values. A lower value of MSE indicates a better model. R-squared (R2) score: It represents the proportion of variance in the target variable that is explained by the independent variables. A higher value of R2 indicates a better model. RMSE: It is the square root of MSE and represents the average distance between the predicted and actual values. A lower value of RMSE indicates a better model.

Random forest regressor is minimum mse 0.1255 and maximum r2_Score with 0.9685 as compared to the linear regression and the other two algorithms give more error as compared to the random forest, the overall best algorithm is random forest regressor because it has better training accuracy, testing accuracy, less mean squared error and also great r2_score of all the ML algorithm. After applying the best ML model make a user interface to predict the surface roughness by using the saved model.

All the actual and predicted data are shown by the graph in Figure 9 in different machine learning algorithms. This graph shows a graphical representation of all detailed understanding of the actual and predicted data.

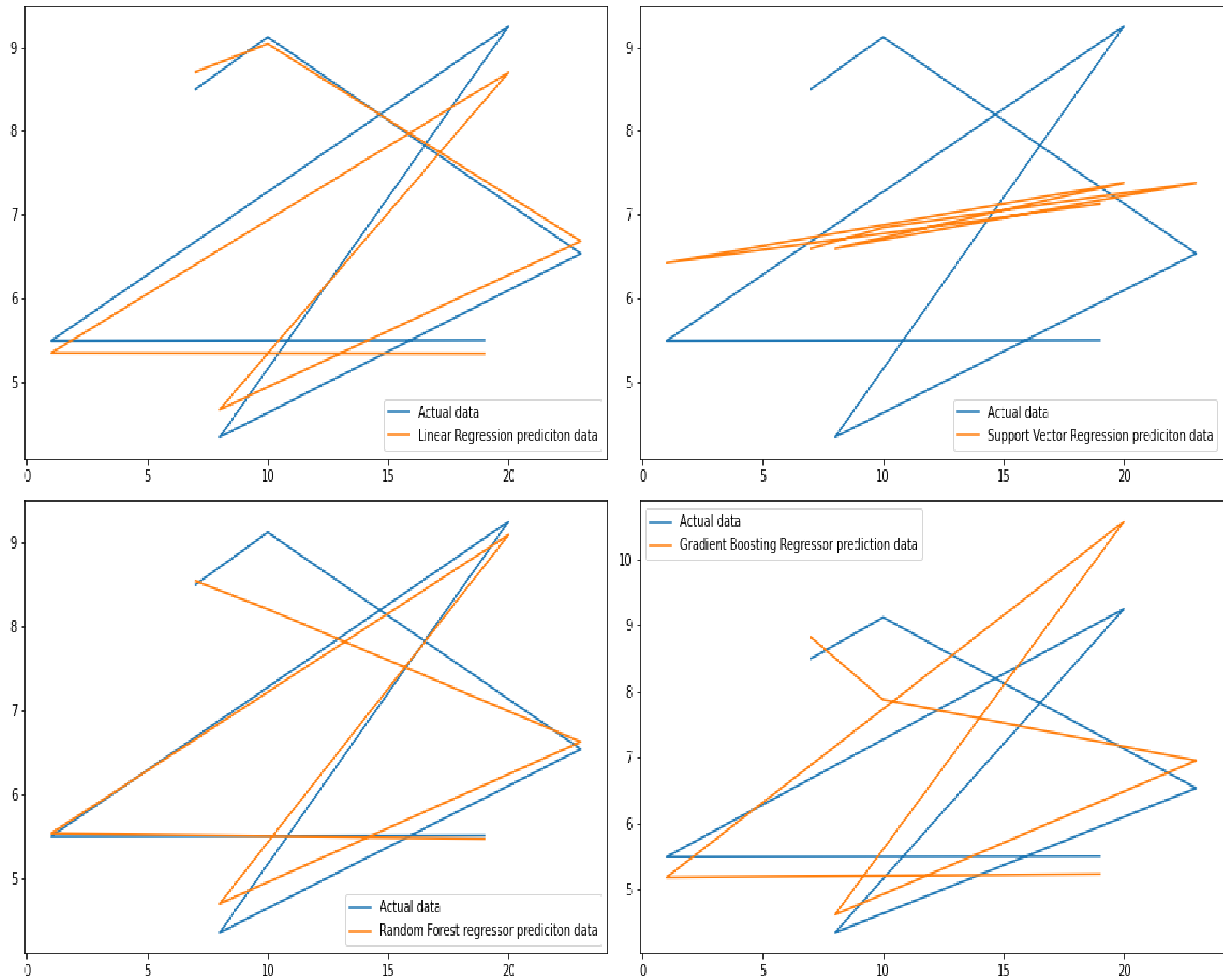

Fig 9. Graphical representation of actual data and predicted data of different machine learning algorithm

Random forest regression algorithm gives the prediction result of the experimental data with minimize error, overall all the 4 machine learning algorithm. All the code of the machine learning is written in jupyter notebook and fig. 9 is coding generated graphical representation of all machine learning

5. Conclusions and future works

The surface roughness was measured and 3D samples were fabricated successfully using the L25 orthogonal array. The study proposed a data-driven framework that utilized machine learning to predict surface roughness and dimensional accuracy, and obtain optimal process parameters. Verification experiments showed that the optimized results were consistent with experimental results, indicating the effectiveness and feasibility of the proposed method. The study concluded that using machine learning to study process parameters and obtain optimal settings for surface roughness is a viable approach.

1. Surface roughness is directly depend on the parameters of layer height and printing speed, With the increase of layer height, Printing speed, that directly effect to increase the surface roughness of the 3d printing parts. Layer height is 89% positive correlation with the surface roughness and printing speed is 30% correlation with the surface roughness. Surface roughness is minimum gives less wear with the meshing parts
2. Infill density and nozzle temperature gives constant relation between the surface roughness's does not gives any type of effect in the surface roughness. Its approx. 0.030 % correlation with the surface roughness.
3. An ensemble machine learning algorithm random forest repressor is less MSE approx. 0.1255 and maximum r2_Score approx. 0.9685 in all the used machine learning algorithm, with training accuracy is 94.45 and testing accuracy 0.9685 which is also shown in the visualization graph in the figure number 9.

Upcoming work involves collecting more data to increase the robustness of the models. Furthermore, new input parameters such as nozzle diameter will be incorporated. Additionally, experimental data will also be utilized in conjunction with or in lieu of numerically generated data to enhance the predictive models.

References:

[1] "IannGibsonn· DaviddRosen BrenttStucker Additive Manufacturing Technologies 3D Printing, Rapid Prototyping, and Direct Digital Manufacturing Second Edition."

[2] S. Ford and M. Despeisse, "Additive manufacturing and sustainability: an exploratory study of the advantages and challenges," *J Clean Prod*, vol. 137, pp. 1573–1587, Nov. 2016, doi: 10.1016/j.jclepro.2016.04.150.

[3] Y. Deshpande, A. Andhare, and N. K. Sahu, "Estimation of surface roughness using cutting parameters, force, sound, and vibration in turning of Inconel 718," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 39, no. 12, pp. 5087–5096, Dec. 2017, doi: 10.1007/s40430-017-0819-4.

[4] D. Wu, Y. Wei, and J. Terpenny, "Surface Roughness Prediction in Additive Manufacturing Using Machine Learning," 2018. [Online]. Available: http://www.asme.org/about-asme/terms-of-use

[5] B. N. Turner, R. Strong, and S. A. Gold, "A review of melt extrusion additive manufacturing processes: I. Process design and modeling," *Rapid Prototyping Journal*, vol. 20, no. 3. Emerald Group Publishing Ltd., pp. 192–204, 2014. doi: 10.1108/RPJ-01-2013-0012.

[6] U. Shaha, "Optimizing Process Parameters of FDM Printer using Design of Experiments Method," *International Research Journal of Engineering and Technology*, 2021, [Online]. Available: www.irjet.net

[7] F. Lavecchia, M. G. Guerra, and L. M. Galantucci, "Chemical vapor treatment to improve surface finish of 3D printed polylactic acid (PLA) parts realized by fused filament fabrication," *Progress in Additive Manufacturing*, vol. 7, no. 1, pp. 65–75, Feb. 2022, doi: 10.1007/s40964-021-00213-2.

[8] P. K. Rao, J. Liu, D. Roberson, Z. Kong, and C. Williams, "Online Real-Time Quality Monitoring in Additive Manufacturing Processes Using Heterogeneous Sensors," *Journal of Manufacturing Science and Engineering, Transactions of the ASME*, vol. 137, no. 6, Dec. 2015, doi: 10.1115/1.4029823.

[9] R. Anitha, S. Arunachalam, and P. Radhakrishnan, “Critical parameters in¯uencing the quality of prototypes in fused deposition modelling.”

[10] D. Popescu, A. Zapciu, C. Amza, F. Baciu, and R. Marinescu, “FDM process parameters influence over the mechanical properties of polymer specimens: A review,” *Polym Test*, vol. 69, pp. 157–166, Aug. 2018, doi: 10.1016/j.polymertesting.2018.05.020.

[11] M. Domingo-Espin, J. M. Puigoriol-Forcada, A. A. Garcia-Granada, J. Llumà, S. Borros, and G. Reyes, “Mechanical property characterization and simulation of fused deposition modeling Polycarbonate parts,” *Mater Des*, vol. 83, pp. 670–677, Oct. 2015, doi: 10.1016/j.matdes.2015.06.074.

[12] S. Nasiri and M. R. Khosravani, “Machine learning in predicting mechanical behavior of additively manufactured parts,” *Journal of Materials Research and Technology*, vol. 14, pp. 1137–1153, Sep. 2021, doi: 10.1016/j.jmrt.2021.07.004.

[13] M. A. Mahmood, A. I. Visan, C. Ristoscu, and I. N. Mihailescu, “Artificial neural network algorithms for 3D printing,” *Materials*, vol. 14, no. 1. MDPI AG, pp. 1–29, Jan. 01, 2021. doi: 10.3390/ma14010163.

[14] S. K. Everton, M. Hirsch, P. I. Stavroulakis, R. K. Leach, and A. T. Clare, “Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing,” *Materials and Design*, vol. 95. Elsevier Ltd, pp. 431–445, Apr. 05, 2016. doi: 10.1016/j.matdes.2016.01.099.

[15] A. Boschetto, V. Giordano, and F. Veniali, “3D roughness profile model in fused deposition modelling,” *Rapid Prototyp J*, vol. 19, no. 4, pp. 240–252, 2013, doi: 10.1108/13552541311323254.

[16] A. Boschetto and L. Bottini, “Roughness prediction in coupled operations of fused deposition modeling and barrel finishing,” *J Mater Process Technol*, vol. 219, pp. 181–192, 2015, doi: 10.1016/j.jmatprotec.2014.12.021.

[17] P. Reeves and ac Cobb, “REDUCING THE SURFACE DEVIATION OF STREOLITHOGRAPHY USING AN ALTERNATIVE BUILD STRATERGY.”

[18] D. Ahn, H. Kim, and S. Lee, “Surface roughness prediction using measured data and interpolation in layered manufacturing,” *J Mater Process Technol*, vol. 209, no. 2, pp. 664–671, Jan. 2009, doi: 10.1016/j.jmatprotec.2008.02.050.

[19] S. B. Mishra, R. Malik, and S. S. Mahapatra, “Effect of External Perimeter on Flexural Strength of FDM Build Parts,” *Arab J Sci Eng*, vol. 42, no. 11, pp. 4587–4595, Nov. 2017, doi: 10.1007/s13369-017-2598-8.

[20] S. B. Mishra, K. Abhishek, M. P. Satapathy, and S. S. Mahapatra, “Parametric Appraisal of Compressive Strength of FDM Build Parts,” in *Materials Today: Proceedings*, Elsevier Ltd, 2017, pp. 9456–9460. doi: 10.1016/j.matpr.2017.06.203.

[21] M. R. Henderson, B. Vasudevarao, D. Prakash Natarajan, M. Henderson, and A. Razdan, “Sensitivity Of Rp Surface Finish To Process Parameter Variation,” 2000. [Online]. Available: https://www.researchgate.net/publication/2467464

[22] A. Garg, A. Bhattacharya, and A. Batish, “On Surface Finish and Dimensional Accuracy of FDM Parts after Cold Vapor Treatment,” *Materials and Manufacturing Processes*, vol. 31, no. 4, pp. 522–529, Mar. 2016, doi: 10.1080/10426914.2015.1070425.

[23] D. Horvath, R. Noorani, and M. Mendelson, “Improvement of Surface Roughness on ABS 400 Polymer Using Design of Experiments (DOE),” *Materials Science Forum*, vol. 561–565, pp. 2389–2392, Oct. 2007, doi: 10.4028/www.scientific.net/msf.561-565.2389.

[24] C. J. Luis Pérez, “Analysis of the surface roughness and dimensional accuracy capability of fused deposition modelling processes,” *Int J Prod Res*, vol. 40, no. 12, pp. 2865–2881, Aug. 2002, doi: 10.1080/00207540210146099.

[25] J. Zhang, P. Wang, and R. X. Gao, “Deep learning-based tensile strength prediction in fused deposition modeling,” *Comput Ind*, vol. 107, pp. 11–21, May 2019, doi: 10.1016/j.compind.2019.01.011.

[26] R. A. Ilyas *et al.*, “Natural Fiber-Reinforced Polylactic Acid, Polylactic Acid Blends and Their Composites for Advanced Applications,” *Polymers*, vol. 14, no. 1. MDPI, Jan. 01, 2022. doi: 10.3390/polym14010202.

[27] R. A. Wach, P. Wolszczak, and A. Adamus-Wlodarczyk, "Enhancement of Mechanical Properties of FDM-PLA Parts via Thermal Annealing," *Macromol Mater Eng*, vol. 303, no. 9, Sep. 2018, doi: 10.1002/mame.201800169.

[28] F. Yu, T. Liu, X. Zhao, X. Yu, A. Lu, and J. Wang, "Effects of talc on the mechanical and thermal properties of polylactide," *J Appl Polym Sci*, vol. 125, no. SUPPL. 2, Sep. 2012, doi: 10.1002/app.36260.

[29] B. Wittbrodt and J. M. Pearce, "The effects of PLA color on material properties of 3-D printed components," *Addit Manuf*, vol. 8, pp. 110–116, Oct. 2015, doi: 10.1016/j.addma.2015.09.006.

[30] M. F. Gonzalez, R. A. Ruseckaite, and T. R. Cuadrado, "Structural Changes of Polylactic-Acid (PLA) Microspheres under Hydrolytic Degradation," 1999.

[31] O. Y. Venkatasubbareddy, P. Siddikali, and S. M. Saleem, "Improving the Dimensional Accuracy And Surface Roughness of Fdm Parts Using Optimization Techniques," *IOSR Journal of Mechanical and Civil Engineering*, vol. 16, no. 053, pp. 18–22, Dec. 2016, doi: 10.9790/1684-16053041822.