

OPTIMIZATION OF LASER PROCESS PARAMETERS USING MACHINE LEARNING ALGORITHMS AND PERFORMANCE COMPARISON

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Abstract

Laser powder bed fusion (L-PBF) can be used to produce near net-shaped functional metal components. Despite offering high flexibility in producing components with intricate geometries, L-PBF has many constraints in terms of controllability and repeatability because of large number of processing parameters. There is a need for a robust computational model which can predict the properties of L-PBF parts using a wide range of processing parameters. In this work, several Machine learning-based algorithms like Random Forest, k Nearest Neighbors, XGBOOST, Support Vector Machine (SVM), and Deep Neural Networks are used to model the property-processing parameters relation for SS 316L samples prepared by LPBF. Laser power, scan speed, hatch spacing, scan strategy, volumetric energy density, and density are used as the input to these models. The developed model is then used to predict and analyze the surface roughness of as-fabricated SS 316L specimens. The prediction and experimental results are compared for the above-mentioned models to evaluate the capabilities and accuracy of each model.

Keywords: Laser Powder Bed Fusion, Neural Networks, Machine Learning, SS316L

1. Introduction

SS 316L is a low carbon austenitic stainless-steel variant that offers great corrosion resistance, creep resistance, and tensile strength at elevated temperatures [1]. Due to its characteristics, SS 316L is widely used for applications in surgical instruments, petroleum refining equipment, heat exchanger tubes, medical implants [2]. Additive manufacturing (AM) has been a topic of interest to many researchers in metal processing as it offers flexibility in the designing and fabrication of intricate geometries [3]. Various metal additive manufacturing processes being developed are binder jetting, direct energy deposition and laser powder bed fusion. Among these techniques, LPBF provides better precision due to fusion of thin powder layers. Numerous studies have reported the additive manufacturing (AM) of SS 316 L components via the LPBF Technique [1,2,5].

In LPBF, a layer of metal powder is spread on the build plate using a re-coater blade and is melted selectively using a laser power source. The Computer Aided Design (CAD) file of the component is sliced into code to program the laser heat source path. LPBF process depends on various processing parameters like laser power, scan speed, scan strategy, and layer thickness. The relationship between these processing parameters and the properties is complicated as LPBF involves multi-physics and multi-scale processes [4]. Tucho et al [5] reported the effect of energy density on part quality in terms of surface roughness, hardness, and strength of SS 316L. Mehrpouya et al [6] performed the optimization of process parameters and their effect on tensile

strength of NiTi alloy. The significant evolution of computer models has improved the understanding of LPBF [7]. With the progress in Machine learning (ML) and Artificial Intelligence (AI), researchers have reported various studies like anomaly detection, defect classification, and process parameters optimization, using traditional ML algorithms and Deep Neural Networks.

Scime et al [8] have presented an algorithm that implements ML and Computer Vision (CV) techniques to detect and classify the enumerated anomalies during powder spreading in the L-PBF process. Gobert et al [9] developed an in-situ defect detection strategy for LPBF using a supervised ML algorithm and to find the porosity, and incomplete fusion location with an accuracy of over 80%. Rong-Ji et al [10] determined the best process parameters set to fabricate metal parts with a higher level of accuracy using a combination of a Genetic algorithm and a Backpropagation Neural Network (NN) algorithm. Ravichander et al [11] employed an Artificial Neural Network (ANN) modeling with various algorithms to estimate the process outputs namely the sample height and surface hardness using parameters like laser power, hatch spacing, and scanning speed. They found that higher scanning speed resulted in lower sample height. Khorasani et al [12] used a Multi-layer Perceptron (MLP) NN to predict the average surface roughness and found that heat treatment and laser power are the greatest influential factors on the surface roughness. Sood et al [13] reported the prediction of compressive strength using process parameters as inputs to a back propagation-based ANN and were able to explain 96.13% of the variability in the response data. Wang et al [14] modeled an ANN with a feed-forward topology and back propagation algorithm to study the effect of process parameters on density and reported that, density was in direct proportion with laser power and ambient temperature and inverse proportion with layer thickness, scan speed, and hatch spacing.

Although the data driven neural networks have the capability of modeling the nonlinear relationship between the process parameters and properties, having small data sets is one of the major issues leading to the problems of overfitting and underfitting [4]. Traditional ML algorithms like XGBOOST [15], Support Vector Machines [16], and Random Forest regressor [17] have proven to perform better than Deep Neural Networks when the amount of data is relatively less [18]. In this study, we compare the performance of traditional ML algorithms with a MLP neural network in modeling the relationship between the process parameters and surface roughness of SS 316L samples made by LPBF. The process parameters selected for this study are laser power, scan strategy, scan speed, hatch spacing, density and Volumetric Energy Density (VED). Mean Squared Error, and Co-efficient of Determination (R² Score) are used as the performance metrics for the ML models.

2. Materials and Methods

2.1 Design of Experiments

The Taguchi mixed-level design was established with the help of Minitab V21 (Minitab Inc.). The layer thickness was constant (30 μm) to simplify the fabrication process. However, a range of effective process parameters were considered in this work, as listed in Table 1. The energy density for different sets of process parameters were calculated using the formula [25]:

$$E_v = \frac{LP}{SS \times HS \times LT} \quad (1)$$

where E_v (J/mm^3) is the energy density, LP (W) is the laser power, SS (mm/s) is the scanning speed, HS (μm) is the hatch spacing, and LT (μm) is the layer thickness.

Table 1: Complete DOE based on Taguchi's mixed-level design

Sample No.	Scan Strategy	Laser Power (W)	Scan Speed (mm/s)	Hatch Spacing (μm)	Energy Density (J/mm^3)
1	Stripes	150	710	111	63.44
2	Stripes	150	770	117	55.50
3	Stripes	150	830	123	48.98
4	Stripes	150	890	129	43.55
5	Stripes	185	710	111	78.25
6	Stripes	185	770	117	68.45
7	Stripes	185	830	123	60.40
8	Stripes	185	890	129	53.71
9	Stripes	220	710	117	88.28
10	Stripes	220	770	111	85.80
11	Stripes	220	830	129	68.49
12	Stripes	220	890	123	66.99
13	Stripes	255	710	117	102.32
14	Stripes	255	770	111	99.45
15	Stripes	255	830	129	79.39
16	Stripes	255	890	123	77.65
17	Chess	150	710	129	54.59
18	Chess	150	770	123	52.79
19	Chess	150	830	117	51.49
20	Chess	150	890	111	50.61
21	Chess	185	710	129	67.33
22	Chess	185	770	123	65.11
23	Chess	185	830	117	63.50
24	Chess	185	890	111	62.42
25	Chess	220	710	123	83.97
26	Chess	220	770	129	73.83
27	Chess	220	830	111	79.60
28	Chess	220	890	117	70.42
29	Chess	255	710	123	97.33

30	Chess	255	770	129	85.57
31	Chess	255	830	111	92.26
32	Chess	255	890	117	81.63

2.2 Powder Preparation and Fabrication

A total of 32 cubical SS 316L specimens of dimensions 8 mm X 8 mm X 6 mm were fabricated via the LPBF process using SLM 125 HL printer (SLM Solutions Group AG, Lübeck, Germany). The printer has a printing workspace of 125 mm X 125 mm X 125 mm, and it utilizes energy from single 400 W Ytterbium fiber laser. Gas atomized SS 316L powder acquired from SLM solutions AG is used for printing. The chemical composition and scanning electron microscope (SEM) micrograph of the SS316L powder are shown in Table 2 and Figure 1, respectively.

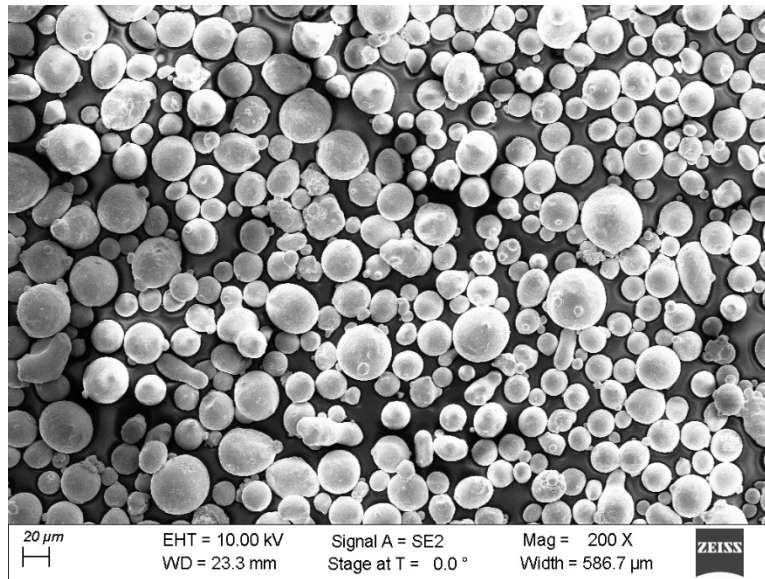


Figure 1. SEM image of fresh SS316L powder particle used for LPBF process

Table 2: The chemical composition of 316L powder

Element	Fe	Cr	Ni	Mo	Nb + Ta	Mn	Si	P	S	C	N	O
Mass fraction (%)	Balance	16-18	10-14	2-3	-	2	1	0.045	0.03	0.03	0.1	-

2.3 Experimental Procedure

The fabricated samples were separated from the build plate with the help of a wire electrical discharge machine (EDM). Surface roughness of the as-printed samples was measured using Keyence VHX-970FN digital microscope (Keyence Corp of America, Itasca, IL, U.S.A). The samples were placed on a sample holder and aligned on the edges in order to maintain the consistency of the measurements. The controller is used to focus on the sample and three

measurements for arithmetic mean roughness (Ra) were taken and the average values are reported. This data is used for both ML algorithms and neural network to make predictions.

2.4 Machine Learning

ML is the ability of a machine to get trained and execute certain tasks without being explicitly programmed. The performance in these tasks is often like how humans solve problems. ML is subclassified into supervised learning, unsupervised learning and reinforcement learning [19]. Supervised learning models are trained with 'labeled data' which allows the model to learn more and improve the accuracy. In unsupervised learning, the model looks for underlying patterns in an 'unlabeled data'. Reinforcement machine learning follows a trial-and-error approach to make the best prediction by establishing a feedback system. Usually, supervised learning models are used in problems like predicting a continuous variable (Regression), classification and clustering as the data consists of labeled classes which are used for predictions. In this study, traditional algorithms like Linear Regression, Random Forest, Support Vector Machine (SVM), k-Nearest Neighbors and XGBoost are used to make predictions of Surface roughness from the experimental data.

2.4.1 Linear Regression

In Linear Regression model, the relationship between input variables (x) and the output variable (y) is assumed to be a linear combination. For example, consider there are n input variables x_1, x_2, \dots, x_n which are used to predict output variable y as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (2)$$

Where $\beta_0, \beta_1, \dots, \beta_n$ are the regression coefficients. The values for these coefficients are found using ordinary least squares. For all known values of input (x), the output variable (y) can be easily predicted. These coefficients denote the influence of each input variable (x) on the output variable (y).

2.4.2 Random Forest

Random Forest [17] is supervised machine learning algorithm which builds decision trees on different samples and takes their average in case of regression problems. Continuous variable handling in data is one of the features of Random Forest regressor. It can be used for both regression and classification problems.

From a learning sample $L = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, random forest uses bootstrap samples to build binary decision trees. The mapping to the learning set is established based on the nature of the problem (classification/ regression).

2.4.3 Support Vector Machine (SVM)

Support Vector Machines (SVMs) are a set of supervised learning models used for both classification, regression and outliers detection. Support Vector Regressor (SVR) is used for the current regression problem. In simple linear regression, the objective function for minimization is,

$$MIN \sum_{i=1}^n (y_i - \beta_i x_i)^2 \quad (3)$$

Where β_i is the regression co-efficient, y_i is the output and x_i is the input feature. In Support Vector Regression, the objective is to minimize the coefficient vector. The error term is handled in constraints as maximum error ε . The optimization problem is formulated as

$$MIN \sum_{i=1}^n ||\beta||^2 \quad (4)$$

Constraints:

$$|y_i - \beta_i x_i| \leq \varepsilon \quad (5)$$

SVR model offers the flexibility to define acceptable error and will find an appropriate hyperplane to fit the data. In the current work, other algorithms like k-Nearest Neighbors regressor [20] and eXtreme Gradient Boosting (XGBoost) Regressor [15] are also used to compare the performance.

2.5 Artificial Neural Network

Artificial Neural Networks are inspired by the biological neural networks to process the data. The network consists of a collection of artificial neurons termed as ‘nodes’ which are interconnected. Each artificial neuron or node receives information as a signal, then processed information is signaled to other neurons in the network. The output of each neuron is computed by a non-linear function called ‘Activating function’ and expresses it as sum of its inputs. Each neuron is assigned a particular weight which adjusts during the learning process. These neurons are arranged into various layers. Each layer may perform different transformation based on the input to the layer.

A Multi-Layer Perceptron (MLP) is a feed forward Artificial Neural Network. It consists of an input layer, output layer and various hidden layers. The data is fed into input layer and then is processed in the hidden layers where the transformations take place. MLP uses a supervised learning algorithm based on back propagation for training. In the current study, a MLP network with 2 hidden layers is used as shown in fig. 2. The input features to the model are the processing parameters Laser Power, Scan speed, Scan strategy, Hatch spacing, Volumetric Energy Density (VED) and density of the printed samples. The output from the network is the predicted surface roughness of testing samples. The data for 32 samples is split into 60% for training, 20% for validation and 20% for testing. During the training process, network is initialized with random weights at each node. In each training epoch, the weights of neurons are changed according to the amount of error in output compared to the expected result.

Table 2. Characteristics of the MLP network used

Number of Layers	2
Number of neurons	100,70

Activation function	ReLU
Number of epochs	200
Data Division	60-20-20
Framework	Keras, Tensorflow

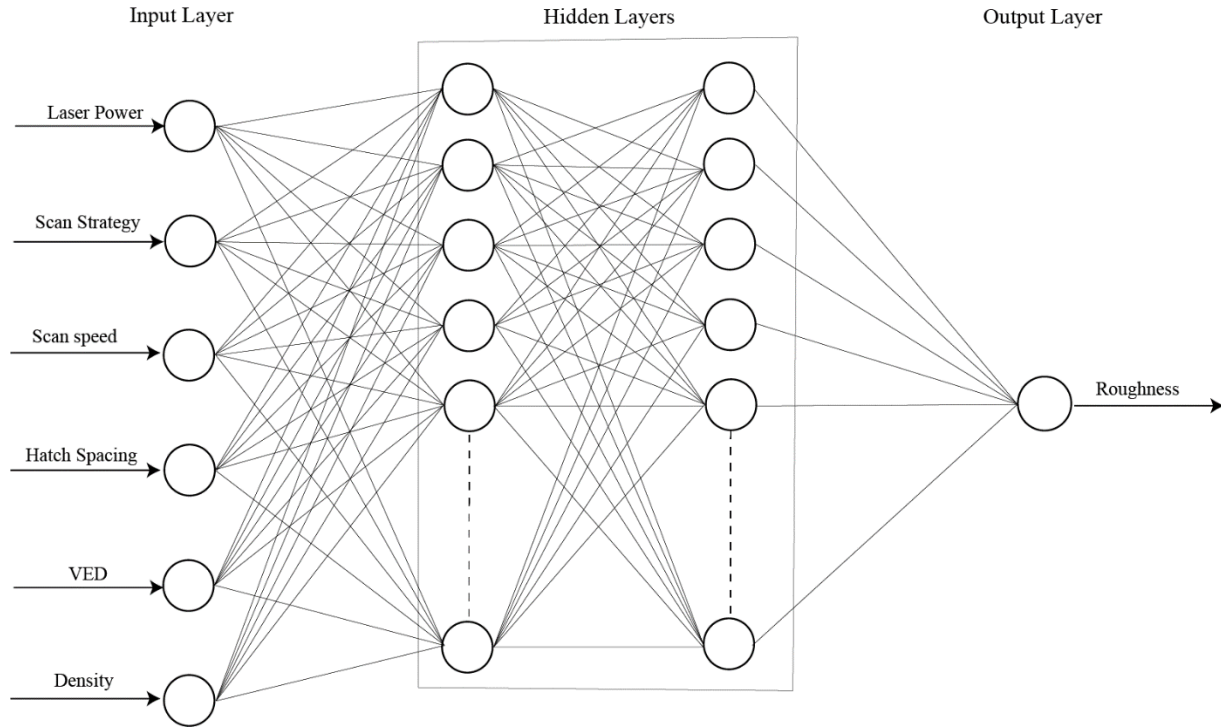


Figure 2. A Multi-Layer Perceptron Network with 2 Hidden Layers

2.6 Error Metrics

In regression problems, the result is often defined based on the error which shows how close the predicted value is to the original value. In the present study, the performance of the machine learning model is assessed using Mean Squared Error (MSE) and Coefficient of Determination (R^2 score) as error metrics. Let us consider \hat{Y} is a vector of n predictions is generated using the machine learning models and Y is the vector of observed values (original).

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (6)$$

$$R^2 \text{ Score} = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (7)$$

R^2 is a measure of goodness of fit of a model. It is a robust metric in evaluating the performance of any statistical model. MSE indicates the mean of square of deviations of the model. For a better

performance, a model should produce less MSE with R^2 score close to 1. MSE can never be negative as it is square of deviations and R^2 can be negative indicating a poor fit to the data.

3. Results and Discussion

The data from the experiments is tabulated and is used for training the machine learning models. Out of 32 samples data for surface roughness, 80% of the data is selected randomly for training the models using train test split function from scikit-learn library [16]. Initial data analysis is performed to understand the input parameters influence on the surface roughness.

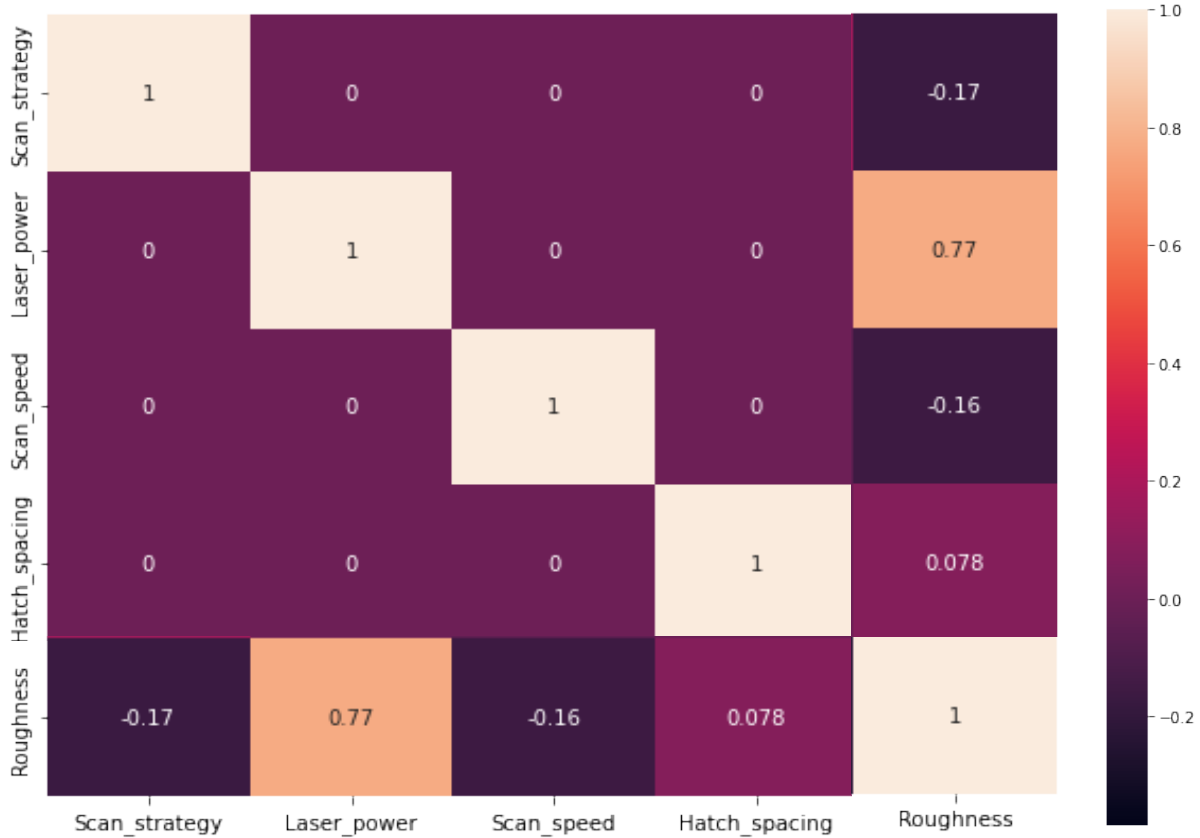


Figure 3. Correlation Matrix of Surface Roughness (R_a) with Processing Parameters

A correlation matrix is a statistical indicator of how two variables are related. A negative value indicates the inverse relationship and maximum value is 1. From Figure 3, laser power had strong linear relationship with surface roughness. Scan speed had a negative correlation to roughness indicating a inverse relationship. The combined effect of laser power and scan speed can be attributed as Volumetric Energy Density (VED). Higher laser power and lower scan speed result in a higher VED. The surface roughness is affected by the surface disruptions caused in the melt pool at higher VED values. The energy from the beam is localized on the powder bed resulting in high temperatures and temperature gradient between the solidifying zone and laser beam eventually creating a shear force on the liquid surface [21]. Similarly, higher values of laser power could result in large amounts of material vaporization and recoil pressure that could lead to melt pool disruptions [22] which in turn increase the surface roughness.

The training data is used for training the traditional machine learning algorithms and the neural networks. In each case, the time required to train the models, MSE and R^2 score is tabulated to compare the performance.

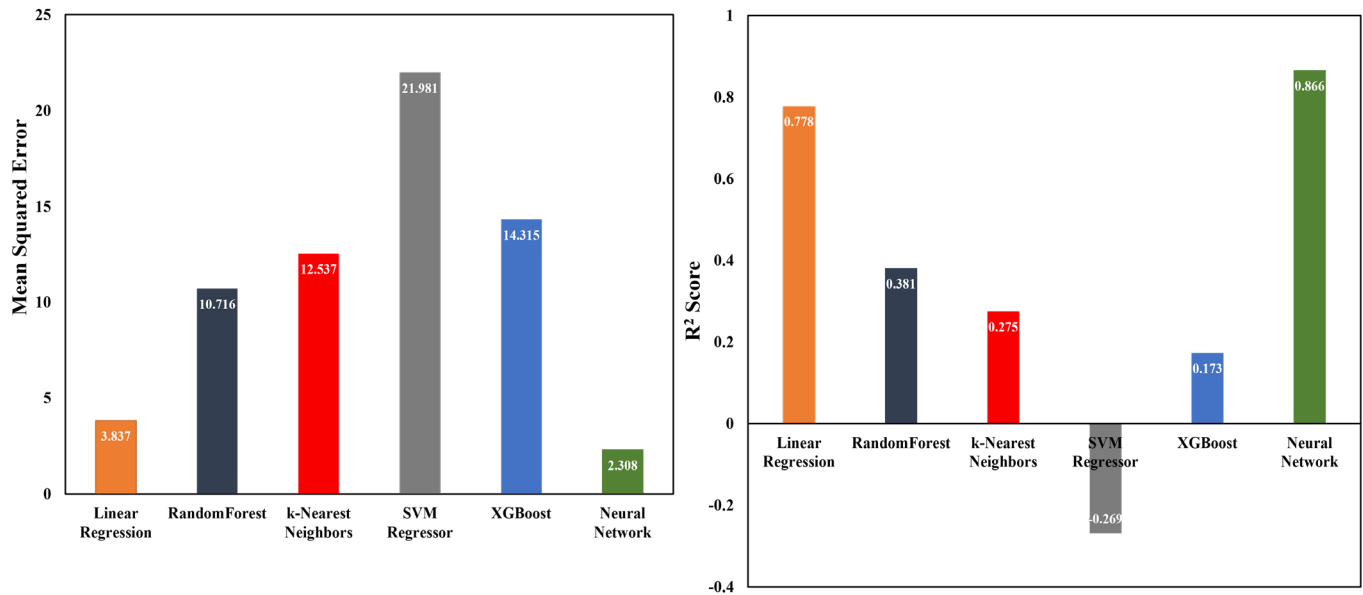


Figure 4. MSE and R^2 score comparison of Machine Learning models

Table 3: Performance of Machine Learning Models and Error Metrics

Model	MSE	R^2 Score	Training Time (ms)
Linear Regression	3.837	0.778	0.01
Random Forest	10.716	0.381	11.995
K-Nearest Neighbors	12.537	0.275	0.1
Support Vector Regressor	21.981	-0.269	0.1
XGBoost	14.315	0.173	31.001
MLP Neural Network	2.308	0.866	3017.43

Figure. 4 shows the performance of traditional machine learning models and a MLP neural network in predicting the surface roughness from the experimental data. Among the traditional machine learning algorithms, Linear Regression model had the least MSE of 3.837. Next best was random Forest regressor with 10.716 MSE. Despite being fundamental algorithm, Linear regression performed well compared to other traditional machine learning algorithms. Random Forest regressor, k-Nearest Neighbors and XGBoost yielded similar MSE values indicating that there is a need for hyperparameters optimization when using these algorithms [2]. Hyperparameters constrain the degrees of freedom of an algorithm and can significantly influence the performance of machine learning model [23]. Comparing the training time, Linear regression was quickest of all models with 0.01 ms. K-Nearest neighbors and Support Vector Regressor were 10 times slower than linear regression due to data mapping. XGBoost regressor works like a neural network with much faster performance. Though it was 100 times faster than a Neural Network, the error was 6 times higher indicating that right set of optimization parameters are required. R^2 score was highest for Linear regression model among the traditional algorithms. Support vector regressor had the

most MSE and poorest fit to the data. This could be due to the inability of SVM model to perform well in lower dimensional spaces [24]. XGBoost and k-Nearest Neighbors algorithms are highly sensitive to outliers in the data which resulted in a poorer fit. Although Random Forest was resource intensive, it had a better fit to the data and lesser MSE when compared to Support vector regressor and k-Nearest Neighbors algorithms. MLP Neural Network with 2 hidden layers yielded the lowest MSE with 2.308 which is 39% better than traditional machine learning algorithm. R^2 score of MLP network was found to be 0.866 which is 11% better indicating a good fit to the data. However, the training time was around 3017.43 ms on a NVIDIA RTX A4000 GPU which was the highest and could be due to the architecture of the network. Neural Networks are computationally intensive algorithms requiring more memory and resources. With an increase in the amount of data, these requirements would eventually shoot up.

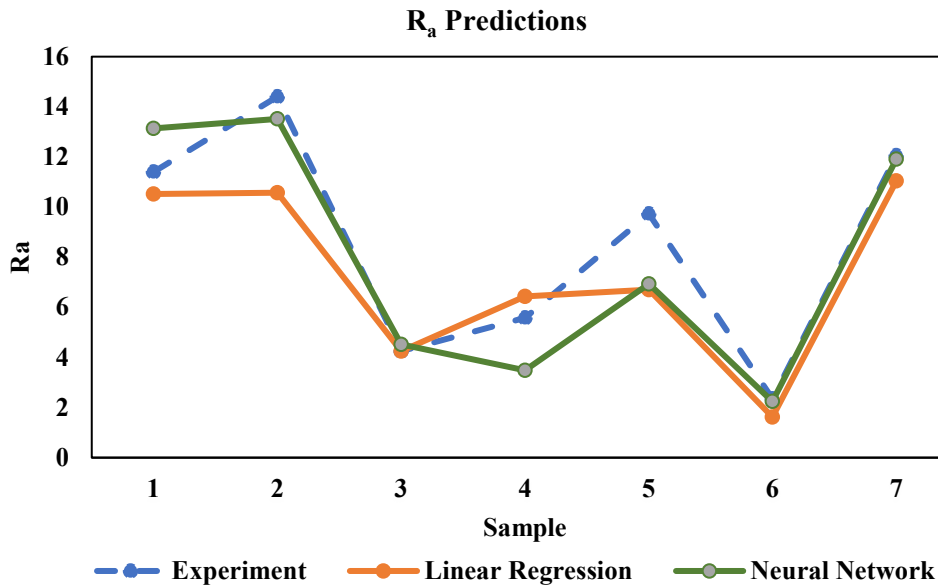


Figure 5. Surface Roughness predictions and comparison with experimental value

Table 4: Comparison of Neural Network and Linear regression Model on Surface Roughness

Sample	R_a (Experimental)	R_a (Linear Regression)	R_a (Neural Network)
1	11.406	10.525	13.141
2	14.403	10.574	13.515
3	4.246	4.255	4.519
4	5.580	6.436	3.487
5	9.723	6.707	6.931
6	2.351	1.622	2.241
7	12.046	11.040	11.906
Mean Deviation		12.32%	8.41%

Figure 5 shows the closeness of predictions from Neural Network and Linear regression model to the experimental surface roughness data. From table 4, predicted surface roughness values from neural network were closer to experimental data than the linear regression. Mean % deviation of MLP network was 8.41 which is 30% lower than Linear regression model.

4. Conclusion

In this work, the performance of various traditional machine learning algorithms and neural networks on surface roughness prediction of SS316L specimens is reviewed. It can be observed that fundamental algorithms like Linear Regression are always a good starting point in data fitting as it had the least MSE of 3.837. Algorithms like Random Forest, XGBoost need more hyperparameter tuning in order to understand the data better and make good fit. Understanding the patterns in data is preferred for models such as k-Nearest Neighbors and XGBoost which are sensitive to outliers. Even though Neural Network consumed 3018 ms of computation time, it is noted that for same amount of data, they had slightly better performance than traditional machine learning algorithms with a MSE of 2.308. With larger amounts of data, Neural network always have an edge over the traditional algorithms like Support Vector machines which are less data intensive. Neural Networks require hyperparameter optimization which can significantly affect the performance of any network.

5. Acknowledgement

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6. References

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