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Experimental Statistical and Explainable Machine Learning Prediction of Surface Roughness in Cryogenically Pre-Cooled Machining of Inconel 718

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Abstract

Cryogenic machining offers a sustainable route for improving the machinability of nickel-based superalloys by reducing thermal loading and improving surface quality. This study develops an experimental-statistical-explainable machine learning framework for predicting surface roughness during cryogenically pre-cooled machining of Inconel 718. Spindle speed, feed rate, and depth of cut were varied through a 20-run face-centered central composite design. Each trial was repeated three times, and surface roughness was measured at three locations. The response surface model explained 91.95% of the measured variation and was used to generate a 1,387-point model-based dataset. Random Forest, Gradient Boosting, Support Vector Regression, XGBoost, and Artificial Neural Network models were compared. To test whether the inputs made non-redundant contributions, an XGBoost feature-ablation study was performed using ten repeated train-test partitions. The full model achieved a mean R^2 of 0.9922 and RMSE of 0.0170 μm . Removing spindle speed produced the largest deterioration ($R^2 = 0.3200$), followed by feed rate ($R^2 = 0.4408$) and depth of cut ($R^2 = 0.6976$). SHAP analysis attributed 41.85% of the global contribution to spindle speed, 37.04% to feed rate, and 21.11% to depth of cut. At the independently tested RSM-optimized condition, XGBoost predicted surface roughness with an error of 4.89%, compared with 8.25% for RSM. The explainability results show how each machining parameter shapes the learned response surface while also demonstrating that predictions remain constrained by the experimental RSM model from which the expanded dataset was generated.

Keywords: Cryogenic pre-cooling; Inconel 718; Surface roughness; Response surface methodology; XGBoost; Ablation study; Explainable artificial intelligence; SHAP.

1. Introduction

Cryogenic machining is now a practical cooling strategy for difficult-to-cut alloys such as nickel-based superalloys, titanium alloys, hardened steels, and aerospace-grade materials. In this approach, liquid nitrogen (LN_2), liquid carbon dioxide (LCO_2), or a similar low-temperature medium is directed near the tool-chip/tool-workpiece interface, where the cutting temperature is normally highest [1-4]. Compared with flood cooling, cryogenic cooling reduces the use of petroleum-based cutting fluids and lowers the related disposal burden. Its localized cooling action also helps suppress tool wear, adhesion, built-up edge formation, and thermal damage on the machined surface [5-8]. Hence, it is useful when tool life, surface finish, dimensional accuracy, chip breakability, and surface integrity are critical [9-11].

Inconel 718 is a representative difficult-to-machine superalloy used in aero-engine components, gas turbines, marine systems, and nuclear applications because it retains strength and corrosion/oxidation resistance at high temperature [12-14]. The same properties create problems

during machining. The low thermal conductivity confines heat near the cutting zone. In addition, high hot strength, work hardening, and chemical affinity with tool materials accelerate flank and notch wear, disturb chip flow, and affect the final surface quality [5,12,15]. These issues make the cooling/lubrication strategy an important part of process selection for Inconel-based alloys.

Earlier studies have reported clear benefits of cryogenic cooling in machining Inconel 718. Pusavec et al. [1] examined surface integrity and reported changes in surface roughness, hardness, and residual stress after cryogenic machining. Kaynak [2] compared dry, MQL, and cryogenic machining and noted lower cutting temperature and tool wear under cryogenic cooling. Musfirah et al. [5] studied high-speed milling in dry and cryogenic environments and reported differences in tool wear, cutting force, and surface integrity. Chaabani et al. [6] further showed that the selected cryogenic medium, LN_2 or LCO_2 , can influence tool wear and the final surface condition during finish turning.

Hybrid approaches have also been explored, including Cryo-MQL, LCO_2 -MQL, electrostatic MQL, and ultrasonic-assisted cryogenic machining. For example, Airao et al. [9] evaluated sustainable cryo-lubrication strategies in turning Inconel 718 and observed reductions in tool wear, surface roughness, power consumption, and specific cutting energy. Danish et al. [8] reported lower surface roughness, cutting temperature, and tool wear for Cryo-MQL compared with dry cutting. Khanna et al. [16] assessed hybrid cooling/lubrication from a sustainability perspective for Ti6Al4V and Inconel 718. More recent studies by Damir et al. [18] and Pereira et al. [19] also linked cooling/lubrication conditions with tool life and surface integrity.

The selected machining parameters also decide the final response. Cutting speed controls heat generation and thermal softening, while feed rate and depth of cut determine chip thickness, cutting load, contact condition, and surface generation. Eskandari et al. [10] optimized cryogenic turning of Inconel 718 using RSM with cutting speed, feed rate, and depth of cut as inputs. Their results showed that cutting speed influenced cutting force, feed rate affected flank wear, and feed rate and depth of cut affected surface roughness. Rubaiee et al. [11] reported that cutting speed, feed rate, and cooling condition jointly affected machining responses during end milling of Inconel 718. Halim et al. [17] also observed a relation between tool edge condition and surface roughness in cryogenic milling. Thus, the machining response is governed by both the cooling strategy and the chosen parameter window.

Process parameters such as spindle speed, feed rate, and depth of cut significantly influence surface roughness because they affect chip formation, tool–workpiece interaction, heat generation, and material removal behaviour. Although conventional statistical approaches such as ANOVA and response surface methodology are useful for identifying the individual and interaction effects of these parameters, machining responses often exhibit nonlinear behaviour due to complex thermo-mechanical interactions [20]. Therefore, recent studies have increasingly adopted machine learning models to establish a data-driven relationship between machining parameters and performance responses.

A Gaussian kernel ridge regression model was previously developed to predict flank wear progression during face milling of Inconel 718 using cutting speed, feed rate, axial depth of cut, and cutting length as input features. The model showed good prediction accuracy and was experimentally validated, demonstrating its suitability for tool wear prediction and machining parameter optimization [21].

A ResNet50-based deep learning model was developed to predict tool wear in machining Inconel 718 using high-resolution images of worn tools. The model showed superior prediction accuracy compared with other deep learning approaches and demonstrated strong potential for real-time tool condition monitoring [22].

An AI-based power consumption prediction strategy was developed for CNC machining of Inconel 718 under MQL and NF-MQL conditions using cutting speed, feed rate, depth of cut, and flow rate as input parameters. Among the tested machine learning models, the Decision Tree algorithm provided the best prediction accuracy, with (R^2) values of 0.915 for MQL and 0.931 for NF-MQL [23].

A predictive modelling and multi-objective optimization study was carried out for WEDM of Inconel 718 using current, pulse duration, and pulse interval as input parameters. ANN provided better prediction accuracy than MLR for machining time, material removal rate, and surface roughness, while MOGA and MCDM methods identified the optimum condition as ($I_p = 2.07$) A, ($T_{on} = 47.30$) μ s, and ($T_{off} = 9.02$) μ s [24].

A machine learning-based study was conducted to predict and optimize power consumption during milling of Inconel 718 under dry, MQL, cryogenic, and cryogenic + MQL conditions. ANOVA showed that cutting speed was the most significant factor affecting energy demand, while Gradient Boosting provided the best prediction performance with (R^2 approx 0.97), supporting the use of ML models for sustainable and energy-efficient machining [25].

A Taguchi-based experimental study investigated the influence of cutting speed, feed, tool, and lubrication parameters on the machining quality of Inconel 718 under MQL conditions. The results showed that a feed rate of 0.10 mm/rev and cutting speed of 70 m/min produced optimum performance, while increased feed rate worsened surface roughness, power consumption, vibration, and tool wear [26].

Cutting forces and tool stresses during machining of Inconel 718 were experimentally and numerically investigated by varying cutting speed, feed rate, and depth of cut. FEM results showed possible notch/flank wear regions on the cutting insert, while ANN modelling accurately predicted tool stresses with (R^2) values close to 1 [27].

RSM and Random Forest models were applied to predict micro-hole drilling responses of Inconel 718 using drill diameter, spindle speed, and feed speed as input parameters. The RF model showed superior accuracy for MRR prediction with ($R^2 = 0.9953$), while RSM performed better for hole entry failure, overcut, and taper ratio predictions [28].

Unlike continuous cryogenic cooling, the present work adopts cryogenic pre-cooling, in which the Inconel 718 workpiece is cooled using liquid nitrogen before machining. Spindle speed, feed rate, and depth of cut are used as input variables, and surface roughness is treated as the output. The study first quantifies parameter effects using RSM and compares the regression predictions with experimental measurements. The validated equation is then used to generate a model-based response surface for comparative ML modelling. The additional contribution is a feature-ablation study and SHAP-based explainability analysis that determine whether each input provides non-redundant predictive information and reveal the magnitude and direction of its contribution. The analysis is deliberately interpreted within the validated experimental domain because the expanded dataset inherits the structure and uncertainty of the fitted RSM equation.

2. Experimental Details

The experiments were carried out using the same machine tool, setup, equipment, and measurement procedure reported in [29]. Unlike the earlier work, the present study used a fresh set of spindle speed, feed rate, and depth of cut values to examine an additional part of the machining window. Surface roughness (Ra) was selected as the response. Table 1 gives the three parameter levels used in the study. The levels were fixed after considering the tool insert manufacturer's recommendations and earlier machining reports.

Table 1. Machining Parameters and the levels

	SS (rpm)	FR (mm/rev)	DoC (mm)
Low	100	0.7	0.25
Medium	350	1.0	0.35
High	600	1.3	0.45

3. Design of Experiments (DoE)

Spindle speed, feed rate, and depth of cut were arranged using an RSM-based design of experiments. A face-centered central composite design was adopted, resulting in 20 trials. This design was preferred because it permits estimation of linear, interaction, and quadratic terms without requiring a very large number of machining experiments. Each trial was repeated three times. For each machined surface, Ra was measured at three locations, and the mean value was used in the analysis. Table 2 reports the input combinations, the three Ra readings, mean Ra, and standard deviation.

Table 2. Experimental Trials and Surface Roughness Measurements (Ra)

Expt. Runs	SS (rpm)	FR (mm/rev)	DoC (mm)	Ra1 (μm)	Ra2 (μm)	Ra3 (μm)	Mean Ra (μm)	Std. Dev.
1	100	1.3	0.25	2.456205	2.1465	2.385	2.33	0.162208502
2	100	1.3	0.45	3.133105	2.6316	2.924	2.90	0.251902735

3	350	1	0.35	1.8162	1.4418	1.602	1.62	0.187847917
4	600	0.7	0.25	1.471755	1.3068	1.452	1.41	0.090077237
5	350	0.7	0.35	1.15408	1.0602	1.178	1.13	0.062266177
6	600	1.3	0.25	1.716555	1.4364	1.596	1.58	0.140530241
7	600	0.7	0.45	1.795355	1.5102	1.678	1.66	0.14331923
8	350	1	0.35	1.8162	1.4418	1.602	1.62	0.187847917
9	350	1	0.35	1.8162	1.4418	1.602	1.62	0.187847917
10	600	1.3	0.45	1.897655	1.7073	1.897	1.83	0.109712917
11	100	0.7	0.45	2.103305	1.7505	1.945	1.93	0.176711672
12	100	1	0.35	2.314575	2.2383	2.487	2.35	0.127410064
13	350	1	0.35	1.8162	1.4418	1.602	1.62	0.187847917
14	350	1	0.35	1.8162	1.4418	1.602	1.62	0.187847917
15	350	1	0.25	1.227975	1.1583	1.287	1.22	0.064423399
16	350	1	0.45	1.770975	1.4823	1.647	1.63	0.144815484
17	100	0.7	0.25	1.491005	1.2348	1.372	1.37	0.128210135
18	350	1	0.35	1.8162	1.4418	1.602	1.62	0.187847917
19	350	1.3	0.35	1.85123	1.5372	1.708	1.70	0.157216578
20	600	1	0.35	0.902	1.278	1.42	1.20	0.267663968

Figure 1 shows the mean Ra obtained from the 20 trials, along with the scatter in repeated measurements. The highest Ra was recorded in Run 2, whereas Run 5 showed the lowest value. In most trials, Ra fell between 1.4 and 2.0 μm . The error bars remain small for several conditions, which indicates acceptable repeatability. The larger scatter in a few runs may be associated with local surface marks or small variations in contact conditions during cutting.

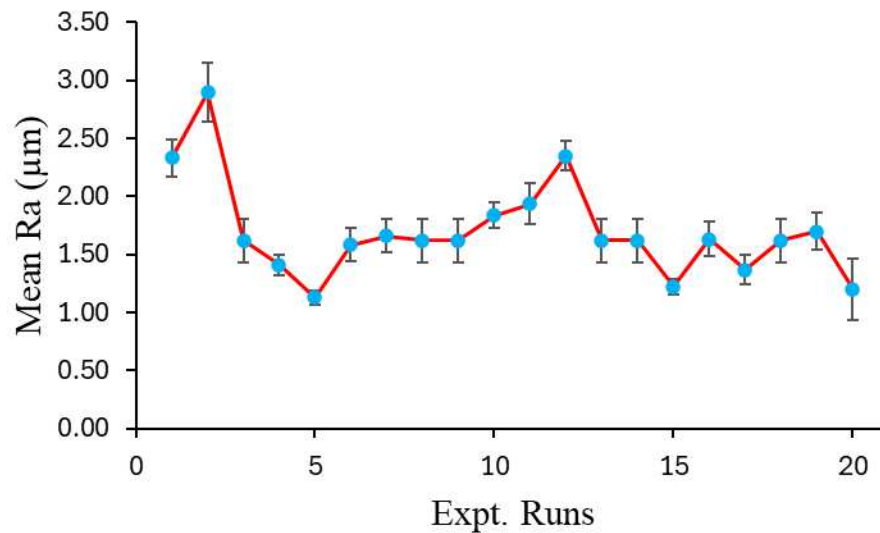


Fig. 1 Mean surface roughness (Ra) for 20 experimental runs, with error bars

4. Introduction to Machine Learning (ML) Methods:

RSM was used first because the number of physical trials was limited and the experiment was planned in a controlled manner. However, the RSM equation still follows a fixed polynomial form. In machining, R_a may vary through coupled effects of speed, feed, and depth of cut, and this behaviour may not always be represented fully by one regression equation. Therefore, ML was used as a second-level prediction tool. The intention was not to replace the experiments, but to check whether nonlinear regression models could improve R_a prediction within the studied parameter range.

Five models were selected to cover different learning mechanisms: Random Forest for tree averaging, Gradient Boosting for sequential residual correction, SVR for kernel-based regression, XGBoost for regularized boosting, and ANN for hidden-layer-based nonlinear mapping. The models were trained and tested using the model-based dataset generated from the experimentally validated ANOVA regression equation. Their predictions were compared using R^2 , RMSE, MAE, and MSE.

4.1. Random Forest Method

Random Forest (RF) was used as the bagging-based baseline model. It builds many decision trees from bootstrapped samples of the training data and averages their outputs for regression. Since each tree is trained on a slightly different subset of data and features, the final averaged prediction is usually more stable than that of a single decision tree [30-34].

For the present problem, RF was useful because it can split the input space without assuming a predefined polynomial form. Spindle speed, feed rate, and depth of cut were supplied as inputs, and R_a was used as the output. After training, the model predicted R_a for the test data by averaging the outputs from all trees. The prediction quality was then quantified using the same error metrics used for the other models.

4.2. Gradient Boosting Method

Gradient Boosting (GB) was used to represent the conventional boosting approach. Unlike RF, the trees are not built independently. The first tree gives an initial prediction, and the following trees are fitted to the remaining errors. In this way, the model progressively corrects its earlier predictions [35-37].

This sequential correction is useful for machining datasets where the effect of one input may depend on the level of another input. In the present study, GB was trained using spindle speed, feed rate, and depth of cut as inputs. The final R_a value was obtained by summing the contributions from the fitted trees, and the test-set prediction error was evaluated using R^2 , RMSE, MAE, and MSE [38,39].

4.3. Support Vector Regression (SVR)

Support Vector Regression (SVR) was included as a kernel-based regression model. SVR searches for a function that keeps prediction errors within a specified tolerance band. With a nonlinear

kernel, the method can represent curved relationships between the input parameters and Ra without explicitly defining a polynomial equation [40-42].

Before training the SVR model, the data were scaled so that the parameters had comparable numerical ranges. The trained model was then used to predict Ra for unseen test combinations. SVR was included mainly to compare a kernel-based approach with the tree-based models and the ANN model [43,44].

4.4. XGBoost Regression

XGBoost was used as the regularized boosting model. It follows the boosting principle, but includes additional control over tree growth, pruning, and regularization. These features help reduce overfitting, especially when the model is trained on structured/tabular data [45-49].

In this study, XGBoost used spindle speed, feed rate, and depth of cut as inputs and Ra as the target. Its inclusion allowed comparison between conventional GB and a more controlled boosting implementation. The trained model was finally checked using both the model-based test set and the optimized experimental condition.

4.5. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) regression was used as the neural-network-based model. The network receives spindle speed, feed rate, and depth of cut at the input layer and returns Ra at the output layer. The hidden layer allows nonlinear mapping between the input parameters and the response [50-54].

During training, the ANN weights were updated to reduce the difference between the predicted and reference Ra values. The trained network was then tested on unseen data. ANN was included to compare a hidden-layer-based method with tree-based and kernel-based regression models.

4.6. Statistical Error Metrics

The accuracy of the ML predictions was evaluated using four metrics: coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean square error (MSE). R^2 describes how closely the predicted values follow the reference values, while RMSE, MAE, and MSE describe the magnitude of the prediction error. The equations used for these metrics are given below [55].

$$R^2 = 1 - \frac{[\sum (y_i - \hat{y}_i)^2]}{[\sum (y_i - \bar{y})^2]} \quad (1)$$

$$RMSE = \sqrt{\left\{ \left(\frac{1}{n} \right) \sum (y_i - \hat{y}_i)^2 \right\}} \quad (2)$$

$$MAE = \left(\frac{1}{n}\right) \sum |y_i - \hat{y}_i| \quad (3)$$

$$MSE = \left(\frac{1}{n}\right) \sum (y_i - \hat{y}_i)^2 \quad (4)$$

where y_i is the reference Ra value, $\hat{y}_i$ is the predicted Ra value, $\bar{y}$ is the mean of the reference Ra values, and n is the number of data points.

4.7 Feature Ablation Study

Feature ablation was used to quantify the predictive information supplied by each machining parameter [56,57]. For reproducibility, 1,387 parameter combinations were regenerated by seeded Latin hypercube sampling within the experimental bounds and their Ra values were calculated using Equation (5). Four XGBoost configurations were evaluated: the full three-input model and three reduced models obtained by removing spindle speed, feed rate, or depth of cut one at a time. For each configuration, the model-based observations were divided into 80% training and 20% testing subsets using ten independent random seeds. Identical partitions were used across the four configurations in each repeat. The models used 700 estimators, a maximum tree depth of 4, a learning rate of 0.03, subsampling and column-sampling ratios of 0.90, and L2 regularization. Performance was reported as the mean and standard deviation of R^2 , RMSE, and MAE across the ten test subsets. A large loss of accuracy after removing a variable indicates that the remaining inputs cannot reconstruct its contribution to the learned response surface.

4.8 Explainable Artificial Intelligence Using SHAP

SHapley Additive exPlanations (SHAP) were calculated for the three-input XGBoost model to explain its predictions [58,59]. TreeSHAP decomposes an individual prediction into the model baseline and additive feature contributions. A positive SHAP value indicates that a parameter raises the predicted Ra relative to the baseline, whereas a negative value indicates a reduction. Global importance was calculated as the mean absolute SHAP value over the held-out test set. Dependence plots were used to examine how the sign and magnitude of the contribution changed across the investigated parameter ranges. Because the ML target values were calculated from Equation (5), SHAP explains how XGBoost reproduced the RSM-derived response surface; it does not provide independent causal evidence beyond the physical experiments.

5. Results and Discussions

5.1 Effect of Machining Parameters on Ra

Figure 2 shows the main effects of spindle speed (SS), feed rate (FR), and depth of cut (DoC) on Ra. Ra decreases as spindle speed increases. A possible reason is improved shearing and reduced material adhesion at the cutting zone under cryogenic cooling. The opposite trend is observed for feed rate and depth of cut. Higher feed increases feed marks and chip load, while a larger depth of cut increases cutting load and material deformation. Within the selected range, the smoother surface was therefore obtained at high spindle speed with low feed rate and low depth of cut.

The observed trend is consistent with earlier reports on cryogenic machining. Akgün and Demir [60] observed lower surface roughness with increasing cutting speed during machining of Inconel 625 and higher Ra at higher feed rate because of increased chip load and surface deformation. Gürbüz and Baday [61] also showed that cryogenic machining conditions and process parameters influence the surface quality of Inconel 718. The present results follow the same general behaviour, although the exact magnitudes are specific to the tool, work material, and parameter range used here.

ANOVA was carried out for Ra to identify the parameters that significantly influenced surface roughness. The detailed ANOVA table is provided in the supplementary material. The regression model gave $R^2 = 91.95\%$, which indicates that the model represents most of the measured Ra variation within the selected machining range. The obtained regression equation is given below:

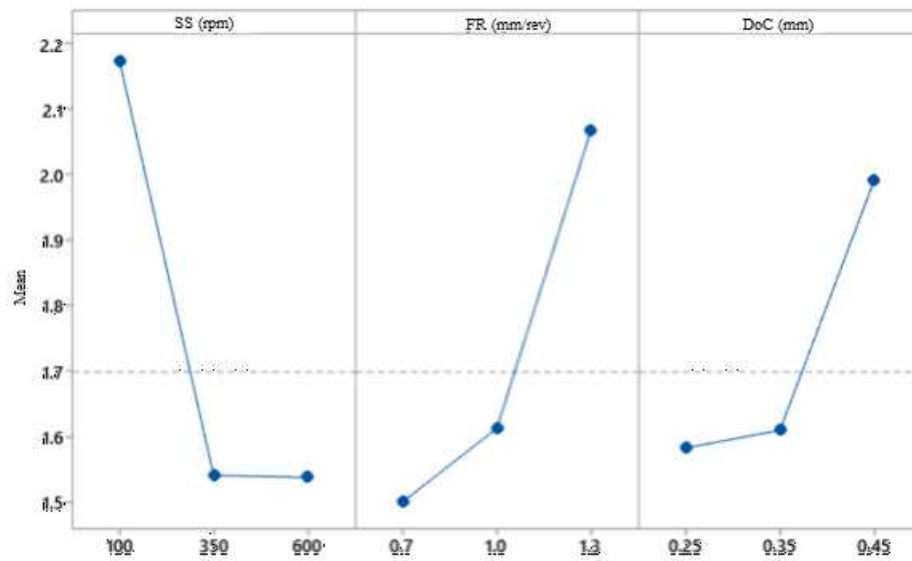


Fig. 2 Main Effect Plot for Ra

$$Ra = -0.70 - 0.001288 * ss + 2.39 * FR + 3.81 * DoC + 0.000007 * SS * SS - 0.412 * FR * FR - 2.29 * DoC * DoC - 0.002635 * SS * FR - 0.00316 * SS * DoC \quad (5)$$

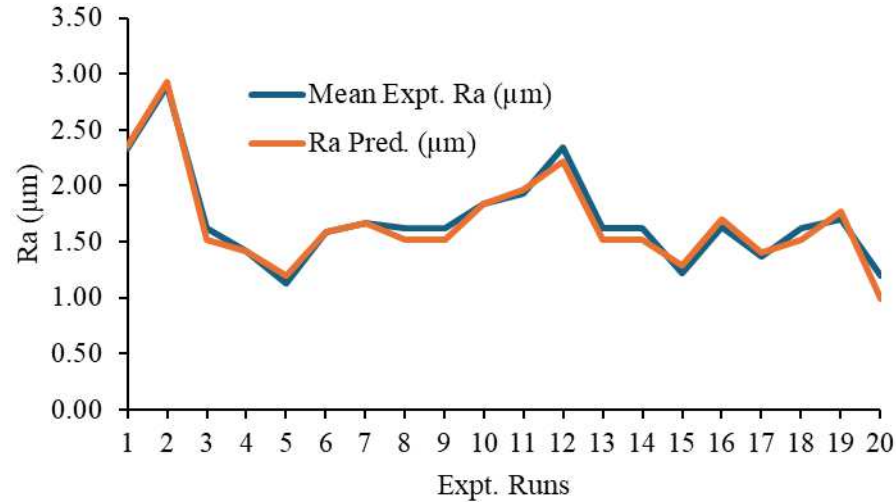


Fig. 3 Comparison of Experimental and ANOVA Regression-Predicted Surface Roughness Values

Figure 3 compares the experimental mean Ra values with the ANOVA-regression predictions. The predicted values follow the measured trend, although a few runs show visible deviations. The agreement was sufficient to use the equation for generating additional input-output combinations. It should be noted that these additional data are model-based values calculated from the validated regression equation. They are not additional experimental readings.

Using the validated equation, spindle speed, feed rate, and depth of cut were varied within the lower and upper limits of the experimental design. The corresponding Ra values were calculated from the regression equation. This produced a 1387-run model-based dataset, which was used for ML model training and testing.

5.2 Machine Learning-Based Modeling and Prediction of Surface Roughness

The 1387-run model-based dataset was then used for ML-based Ra prediction. The dataset contained combinations of spindle speed, feed rate, and depth of cut within the selected machining range, along with regression-calculated Ra values. The three machining parameters were used as inputs, and Ra was used as the target. The data were divided into training and testing subsets, and the five regression models were evaluated using R^2 , RMSE, MAE, and MSE. The Python codes are provided in the supplementary material.

Table 3 Comparison of Error Metrics for Different ML Models

ML Method	R²	RMSE	MAE	MSE
Random Forest	0.995	0.0251	0.0184	0.0006
Gradient Boosting	0.996	0.0173	0.0118	0.0003
SVR	1.0	0.0003	0.0002	0.0000001
Extreme Gradient Boosting	0.998	0.0167	0.0113	0.0003
Artificial Neural Network	0.999	0.0084	0.0067	0.00007

Table 3 compares the performance of the five ML models on the model-based test data. All models produced R² values above 0.995, which shows that the generated Ra values were learned with high accuracy. SVR gave the lowest test-set error, with R² = 1.000, RMSE = 0.0003, and MAE = 0.0002. ANN also showed strong prediction performance, followed by XGBoost, Gradient Boosting, and Random Forest. Since the test data were derived from the validated regression equation, these values mainly indicate how well each model reproduced the equation-generated response surface.

Table 4 Prediction Accuracy of RSM and ML Models at the Optimized Machining Condition

Method	Ra	% Error
Experiment	1.03505	
RSM	0.9497	8.25
Random Forest	0.9789	5.42
Gradient Boosting	0.9788	5.43
SVR	0.9740	5.90
Extreme Gradient Boosting	0.9844	4.89
Artificial Neural Network	0.9722	6.07

Table 4 reports the independent validation at the RSM-optimized condition. The optimized parameters were spindle speed = 357.5758 rpm, feed rate = 0.7 mm/rev, and depth of cut = 0.25 mm. The experiment at this setting gave Ra = 1.035 μm. RSM predicted 0.9497 μm, giving an error of 8.25%. All ML models reduced the error relative to RSM. XGBoost gave the closest value, with Ra = 0.9844 μm and an error of 4.89%. RF and GB gave almost similar errors of 5.42% and 5.43%, while SVR and ANN gave errors of 5.90% and 6.07%. Thus, XGBoost showed the best agreement with the independent optimized experiment.

5.3 Feature Ablation Results

Table 5 summarizes the repeated feature-ablation analysis. The full model retained high and stable predictive accuracy, with mean $R^2 = 0.9922 \pm 0.0016$, $RMSE = 0.0170 \pm 0.0021 \mu m$, and $MAE = 0.0123 \pm 0.0012 \mu m$. Removing spindle speed caused the largest loss of performance: R^2 decreased to 0.3200 and $RMSE$ increased by approximately 9.38 times. Removing feed rate reduced R^2 to 0.4408 and increased $RMSE$ by approximately 8.51 times. The depth-of-cut ablation was less severe but remained substantial, with $R^2 = 0.6976$ and a 6.25-fold increase in $RMSE$. Therefore, none of the three inputs was redundant within the investigated range. The ranking obtained from predictive deterioration was spindle speed, feed rate, and depth of cut.

Table 5 Feature-ablation results for XGBoost across ten repeated train-test partitions

Model configuration	R^2	RMSE (μm)	MAE (μm)
Full model	0.9922 ± 0.0016	0.0170 ± 0.0021	0.0123 ± 0.0012
Without spindle speed	0.3200 ± 0.0592	0.1599 ± 0.0059	0.1280 ± 0.0053
Without feed rate	0.4408 ± 0.0508	0.1450 ± 0.0063	0.1085 ± 0.0043
Without depth of cut	0.6976 ± 0.0340	0.1066 ± 0.0055	0.0819 ± 0.0047

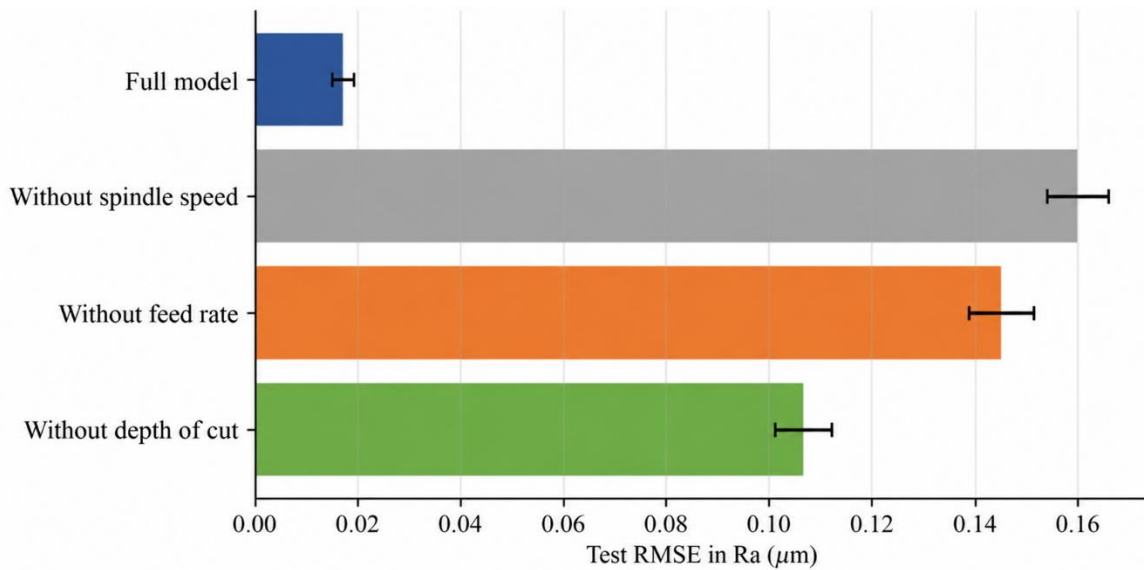


Fig. 4 Feature-ablation performance measured using test-set RMSE. Error bars indicate one standard deviation across ten repeated partitions.

5.4 SHAP-Based Explanation of Surface Roughness Prediction

The fixed-split XGBoost model used for SHAP analysis achieved $R^2 = 0.9920$, $RMSE = 0.0167 \mu m$, and $MAE = 0.0116 \mu m$ on the held-out model-based test set. Table 6 and Figure 5 show the mean absolute SHAP values. Spindle speed had the largest global contribution ($0.1089 \mu m$; 41.85%), followed closely by feed rate ($0.0964 \mu m$; 37.04%). Depth of cut contributed $0.0549 \mu m$ (21.11%). This ranking agrees with the ablation analysis, which strengthens the conclusion that spindle speed and feed rate contain the largest non-redundant contributions to predicted Ra [58].

Table 6 Global SHAP importance of the XGBoost model

Input parameter	Mean SHAP (μm)	Contribution (%)
Spindle speed	0.1089	41.85
Feed rate	0.0964	37.04
Depth of cut	0.0549	21.11

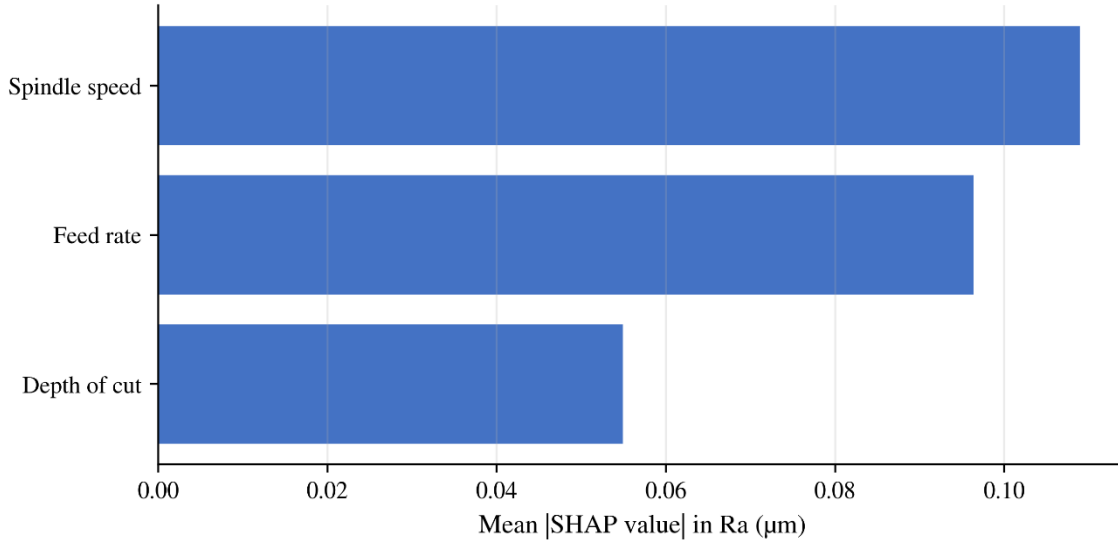


Fig. 5 Global SHAP importance for the XGBoost surface roughness model.

The SHAP dependence plots in Figure 6 clarify the direction of the effects. Increasing spindle speed progressively shifted its contribution toward lower Ra, consistent with improved shearing and reduced adhesion in the selected cryogenic machining window. Higher feed rate shifted the contribution toward higher Ra because of increased feed marks and chip load. Depth of cut showed a smaller but generally positive contribution at higher values, consistent with greater cutting load and material deformation. The spread of SHAP values at a given parameter level reflects interaction effects embedded in Equation (5), particularly the spindle-speed $\times$ feed-rate and spindle-speed $\times$ depth-of-cut terms. These trends are physically consistent with the main-effect analysis, but they should be interpreted as a transparent representation of the fitted response surface rather than proof of causal mechanisms [63].

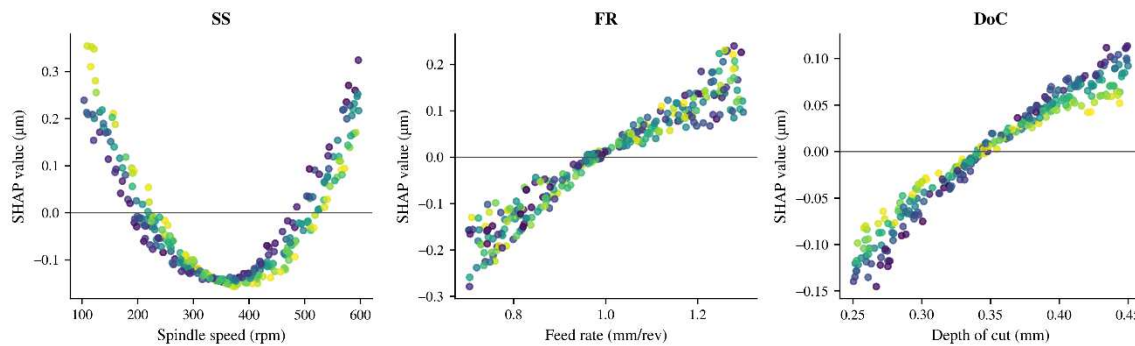


Fig. 6 SHAP dependence of spindle speed, feed rate, and depth of cut. Positive values increase predicted Ra relative to the model baseline; negative values decrease it.

6. Conclusions

This study combined cryogenic pre-cooling experiments, RSM, supervised ML, feature ablation, and SHAP analysis to predict and interpret surface roughness during machining of Inconel 718. The principal findings are as follows:

- Ra decreased with increasing spindle speed, whereas higher feed rate and depth of cut increased Ra within the investigated process window.
- The RSM model explained 91.95% of the experimental Ra variation and provided the bounded response surface used for comparative ML modelling.
- The full XGBoost model achieved a repeated-split mean R^2 of 0.9922 and RMSE of 0.0170 μm on the model-based dataset.
- Ablation showed that spindle speed supplied the largest non-redundant predictive contribution, followed by feed rate and depth of cut. Removing these inputs reduced R^2 to 0.3200, 0.4408, and 0.6976, respectively.
- SHAP assigned 41.85% of the global contribution to spindle speed, 37.04% to feed rate, and 21.11% to depth of cut. The direction of the SHAP effects agreed with the machining trends identified through RSM.
- At the independently tested optimized condition, XGBoost produced the smallest error of 4.89%, compared with 8.25% for RSM.
- The high ML accuracy mainly demonstrates faithful reconstruction of the RSM-derived response surface. The model should therefore be used only within the experimental bounds and should not be interpreted as independently validated over all 1,387 virtual conditions.
- Future work should validate the explainable model using additional machining conditions selected independently of the original design and should include tool wear, cutting force, temperature, and surface-integrity responses.

Clinical trial number: Not applicable

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Disclosure of Interests

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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