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Predictive Modelling of Surface Roughness in Grinding Operations Using Machine Learning Techniques

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This paper details a systematic machine learning workflow designed for the prediction of surface roughness in grinding operations using key machining parameters. Those parameters are Depth of Cut, Feed Rate, Work Speed, and Wheel Speed. The model was trained and validated on a data set which comprised experimental measurements of those parameters and their corresponding values of surface roughness. Three machine learning models, Random Forest, Gradient Boosting, and LightGBM, were developed and evaluated based on accuracy of prediction of the surface roughness. The validation of all three models was performed using performance metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). Among the models, LightGBM exhibited the highest value of performance with the lowest error observed MSE 0.0047, MAE 0.064, and RMSE 0.09 respectively, while an R-squared value closest to zero. (-0.02). The moderate performance was shown by the Random Forest which presented an MSE of 0.0063, MAE of 0.085, and RMSE of 0.10, while the Gradient Boosting recorded the highest error rates which may indicate that it is the least effective model. It is an effective application of machine learning in predicting surface roughness and gives an insight into machining process optimization through predictive modelling.

Keywords: Machine Learning Workflow, Surface Roughness Prediction, Grinding Operations, Machining Parameters, Depth of Cut, Feed Rate.

1 Introduction

Grinding is a precision machining process that employs an abrasive tool to remove unwanted material from workpiece surfaces and thereby provide greater removal rates, superior surface finishes, and longer production runs. Increasingly wide usage of grinding comes from high-precision parts and challenging-to-cut glass ceramics, with special attention paid to its application in the manufacture of telescope mirrors. Prediction models are created by the researchers to analyse the influence exerted by grinding parameters on workpiece characteristics and surface topography [1]. One of the important parameters of product quality, surface roughness has an influence on fatigue, corrosion resistance, performance, and aesthetics. Its value is normally defined in the technical drawings and considered by the process planners at the time of selection of the cutting tools, machine tool equipment, or settings. However, surface roughness is influenced by factors other than the cutting parameters: material, geometry, built-up edges, tool wear, and use of refrigerants [2]. Grinding is one of the most important manufacturing processes in the aerospace, defence, and automotive industries, where highly accurate and durable parts are produced [3]. Some research activities are as follows: sustainability, cutting fluid use, cryogenics, hybrid lubrication, and cooling. Based on grinding force data, [4] describes a method for applying data-driven models for surface roughness prediction. The best model presented was the deep neural network with four hidden layers and FFT features, which had a mean absolute percentage error of 3.17%. The authors further propose an automatic regrinding technique that should be able to identify areas of the workpiece with roughness above the threshold to smooth them accurately. For large-diameter shaft grinding, [5] developed a deep learning-based prediction method for surface roughness. In this architecture, the model fuses several process signals using an attentional CNN-LSTM architecture. The input features used here are spindle current, vibration, and sonic emission signals. Based on the dynamic grinding force model, a new surface roughness forecasting model is presented by [6] in the case of silicon nitride ceramics grinding. The model obtained the MRE of 19.51% for the theoretical and experimental dynamic grinding force values, and the average grinding force has an RE of 9.37%. However, it also yields an MRE of 12.79%, while the random grinding tests proved that the model was valid at 13.65%. The new method to simulate and model wafer grinding surface roughness considering grinding vibration is presented in [7]. The established model creates an iterative dynamics model for the grinding wheel and work piece turntable, reconstructs the surface grain of the gear teeth, and solves dynamic equations. After grinding comparison tests, the highest variation was in a grinding comparison test, which was found to be 5.4% and 7.7%. Based on research on wafer precision grinding technology, this model can be used as a reference.

To calculate the proper cylindrical grinding process factors of austenitic SS304, a material applied both for residential and industrial purposes, [8] has made use of the Taguchi technique in combination with Grey Relational Analysis. Some variables are workpiece speed, longitudinal feed, transverse feed, and coolant flow rate. This work had taken place by designing an L9 orthogonal array under the approach of Taguchi. Grey relational analysis was used to predict the optimal grinding process parameters that satisfy the material removal rate and surface roughness. Besides a standard law of measurement uncertainty distribution and the application of Etalon samples, [9] offers a possibility to have a quick method for the estimation of the surface condition of the roughness error using a secondary standard. For LUVAG of alumina ceramics, [10] offered a predictive model for surface roughness with ensemble learning of SVM. Compared are four modules with four other machine learning approaches. Compared to individual models, the error reductions were 6.3%, 7.9%, 8.9%, and 7.5%. Also, it contains the lowest average ratio of Mean Absolute Error for the prediction of LUVAG surface roughness. By using multilayer graphene platelets and two different cutting fluids (synthetic and semi-synthetic), [11] examines the surface topography and roughness of bearing steel SAE 52100 grinding. From the outcome, the type of base fluid used has a tremendous effect on the grinding performance. When MLG was used as a replacement for the conventional MQL, the value of the Ra parameter got reduced by 9% in semi-synthetic fluid and increased by 29% in synthetic fluid. Specific grinding energy of synthetic and semi-synthetic fluids was reduced by 14% and 7%, respectively, with the presence of MLG. With MLG used for grinding, there was also lesser severe plastic deformation and material adhesion. It uses a hybrid PSO-RDNN algorithm in optimizing machining parameters for finish turning of hardened AISI D2, minimizing the cost, and maximizing tool life while ensuring good surface quality. The neural network predicts tool flank wear with high accuracy ($R^2 = 0.9893$) and surface roughness with high accuracy ($R^2 = 0.9879$). The proposed approach also shows a Pareto optimality graph for optimized cutting conditions [12].

The measurement strategy was seen to affect cylindricity by 100%. It was observed that scanning speed, stylus diameter, and filtering (cut-off 8) are key factors. The workpiece samples possessed Ra 0.28–15.37 μm cylindricity variation CYLtref 5.57–116.96 μm, and three major groups were seen. The lower scanning speed was measured at 5 mm/s to enhance accuracy, as stated in ISO 12180-2:2011 guidelines [13].

The aim of the study is to develop predictive models for surface roughness in grinding operations using machine learning techniques. Formulate a robust predictive framework that can be applied to estimate surface roughness by machining parameters such as DOC, Feed Rate, Work Speed, and Wheel Speed. Although a large number of research studies have analysed the impact of these parameters on surface quality, yet still, there is a wide-open gap to exploit more advance machine learning algorithms aiming to optimize the predictions over a broad range of operational conditions. The actual problem that caused through the research work shows how inconsistent and inaccurate surface roughness prediction in the machining operation can be attained even with the use of certain traditional modelling approaches, as the data turns into complex and nonlinear to model. This work fills the gap by applying state-of-the-art machine learning models, namely Random Forest, Gradient Boosting, and Light GBM, for the prediction of surface roughness, providing manufacturers with more accurate and efficient tools for process control. The paper follows this structure: Section 2 (Methodology): describing the workflow of the whole study, starting from an overview of the dataset used; descriptive statistics of the data; exploratory data analysis aimed at further investigation; building models; performing the training and evaluation procedures; adjusting the hyper parameters on experimental trials; selecting the best model. It goes in detail on how data is dealt with, as well as making various models of machine learning along with the steps performed to optimize its performance. Section 3 Results and Discussion: In the section, it is evaluated and compared based on the performance metrics such as MSE, MAE, RMSE, and R-squared. The paper therefore presents results from exploratory analyses of data as well as the outcome of the models with the final discussion on the effectiveness of the models and the implications in predicting surface roughness.

2 Mathematical Modelling of Path Loss

The methodology used in this research involves a structured machine learning workflow to predict surface roughness using various machining parameters. To ensure systematic development and evaluation of a model, the entire process is broken down into several key steps as mentioned below.

2.1 Understand the Problem

The first step is to define the problem, understand it profoundly, and try to determine the relationships. The most primary objective of this study is the prediction of surface roughness related to machining parameters such as DOC, FR, WRS, and WHS. This recognition of the relationship between these factors and outputs of surface roughness forms a guide in the subsequent analysis steps.

2.2 Data Collection

Following the determination of the problem to be solved, the data relevant to it is gathered. In this paper, the chosen dataset provided the measurements of machining parameters and the values of surface roughness obtained by a few experimental setups. The quality of data and its reliability are to ensure that machine learning models perform well satisfactorily.

The entire data collection process started with preparing the workpiece material made of EN31 metal having a hardness of 50HRC. The workpiece was subjected to various machining processes such as facing, turning, and step turning followed by hot oil deep hardening process. Holes were drilled using EDM within the workpiece for the insertion of thermocouples for temperature measurement. Slip rings were employed for data acquisition purposes, in mounting the workpiece onto a dedicated custom test rig. The experimental setup was attached to an AHG-60X300 CNC grinding machine that provided surface roughness, temperature, and force measurement channels to record forces imposed during face and shoulder grinding operations. Sensors and measurement instruments were used in several configurations to obtain the acquired data to support its analysis.

2.2.1 Dataset Description

Tab. 1 *Machining Parameters and Results*

Depth of Cut (DOC)	Feed Rate (FR)	Work Speed (WRS)	Wheel Speed (WHS)	Surface Roughness (Face)	Surface Roughness (Shoulder)	Temper-ature (Face)	Tempera-ture (Shoulder)
0.0325	1.5	250	1067	1.53	1.51	40.66	43.19
0.0325	1	175	1067	1.62	1.6	39.46	42.9
0.04	1	100	1067	1.52	1.58	38.05	44.87
0.0325	1.5	100	1067	1.29	1.27	41.57	42.76
0.0325	1.5	175	1186	1.41	1.49	42.13	43.88
0.0325	1	175	1067	1.59	1.6	41.86	44.03
0.0325	1	175	1067	1.54	1.52	43.2	40.38
0.0325	0.5	175	1186	1.51	1.54	45.61	43.98

The dataset involved in the study for this research is on specific machine parameters and how the said parameters affect the surface roughness in the grinding process. Therefore, table 1 shows, the parameters examined are DOC, FR, WRS, and WHS, which signify different operational settings of the grinding operation. The surface quality which represents the Surface Roughness (Face) and Surface Roughness (Shoulder), comes out as the outcome of interest. This represents the finish achieved on two distinct areas of the machined workpiece. Through the variety of settings of machine parameters, how alterations in these affect the surface roughness have been captured by the dataset. It allows analysis and modelling of surface roughness behaviour, based on the operational conditions, to predict surface finish from the given machine settings, in a valuable way towards optimization of grinding processes. The fig. 1 depicts the overall machine learning workflow for prediction of surface roughness, commencing with an understanding of the problem and data acquisition, followed by data pre-processing as well as EDA to capture patterns and prepare a dataset. In the process then follows model development, training, and evaluation to make a performance appraisal using appropriate measures. Hyperparameter tuning is performed through methods like grid search or randomized search to optimize the model, finally resulting in the selection of the best-performing model. This iterative process works to develop an accurate and dependable model for prediction of surface roughness.

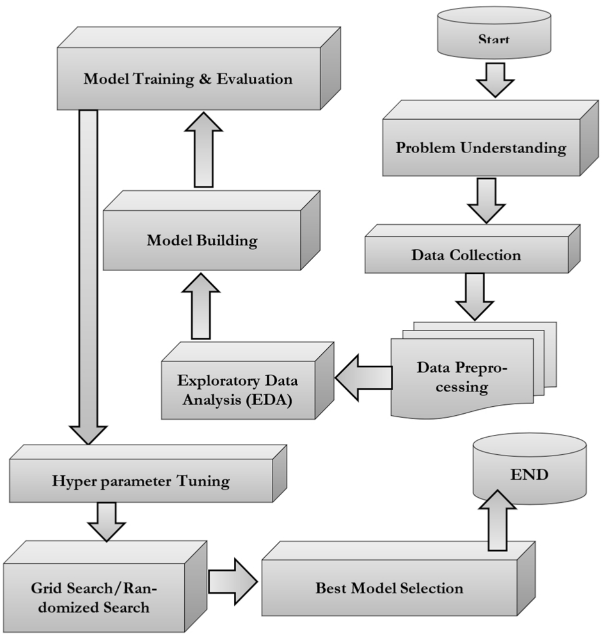

Fig. 1 *Machine Learning Workflow for Surface Roughness Prediction*

2.3 Data Pre-processing

With the data so obtained, it is prepared, pre-processed to be ready for analysis. It includes cleaning the data, especially dealing with values of missing or inconsistent kinds, further removes outliers and encodes categorical variables if necessary. Another crucial step is the splitting of the dataset into training and testing subsets which ensures how the model can be trained without necessarily seeing its performance on unseen data. Features are normalized or scaled appropriately to improve convergence when training the models.

2.4 Exploratory Data Analysis (EDA)

The goal of EDA is to search for patterns, trends, and correlations in the data. For this purpose, descriptive statistics and various forms of visualizations such as correlation heat maps, scatter plots, and box plots are used for a better understanding of the distribution of the data and whether there are associations among the input parameters with the output surface roughness. All the EDA will guide the model-building process and outline important characteristics of the analysis.

2.5 Model Building

Several models are generated in this stage to predict surface roughness given the machining parameters of DOC, FR, WRS, and WHS. Models that are selected will include Random Forest, Gradient Boosting, and Light GBM because they are good at extracting complex, non-linear relationships within the data.

2.5.1 Random Forest

It is an ensemble of decision trees. The result from each tree T_i is combined collectively to get the final prediction $\hat{y}$ [14, 15]. This is done based on the following equation:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{1}$$

Where:

N…The number of trees in the forest and x represents the input features.

2.5.2 Gradient Boosting

This model builds trees sequentially, with each tree f_m correcting the errors of the previous ones [16, 17]. The objective is to minimize a loss function $L(y, \hat{y})$ using gradient descent:

$$f_m(x) = f_m 1(x) - \eta \nabla_{\hat{y}} L(y, \hat{y}) \tag{2}$$

Where:

η…The learning rate,

$\nabla_{\hat{y}}$ …Denotes the gradient of the loss function with respect to the predictions $\hat{y}$.

2.5.3 LightGBM

LightGBM is a variant of gradient boosting, using leaf-wise growth of trees to minimize the objective function:

$$f(x) = \sum_{i=1}^{N} g_i(x) \tag{3}$$

Where:
$g_i(x)$…The prediction of the i-th leaf node,
N…The total number of leaf nodes.

These models are trained using the training subset of the data, where initial hyperparameters are set to default values.

2.6 Model Training & Evaluation

After building the models, they are trained on the training data. During training, each model learns to map the input parameters to the corresponding surface roughness values by minimizing the error between predicted and actual values. Once trained, the models are evaluated on the testing data using performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the R-squared (R^2) score. This evaluation provides insights into how well the models generalize to unseen data [18-21].

$$MSE = \frac{1}{n}\sum_{i-1}^{n}(y_i - \hat{y_i})^2 \tag{4}$$

Where:
n…The number of data points,
y_i…The actual value, and
$\hat{y}$…The predicted value.

After training, the models are evaluated on the testing data using performance metrics such as:

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i-1}^{n}|y_i - \hat{y_i}| \tag{5}$$

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{6}$$

- R-squared:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

Where:
$\bar{y}$…The mean of the observed data.

R2 Measures the proportion of variance in the dependent variable that is predictable from the independent variables.

2.7 Hyperparameter Tuning

To further optimize the models and improve their performance, hyperparameter tuning is conducted. Hyperparameters, which are not learned by the model but set before training (such as the number of trees in Random Forest or the learning rate in Gradient Boosting), are fine-tuned to achieve better predictive accuracy. This step is crucial for maximizing model performance and minimizing errors.

2.8 Grid Search / Randomized Search

Hyperparameter tuning is performed using techniques such as Grid Search and Randomized Search:

2.8.1 Grid Search

Grid search involves systematically evaluating every combination of a predefined hyperparameter grid. For example, for a Random Forest, if the grid contains:

$$N \in \{100,200,300\}, d \in \{10,20,30\} \tag{8}$$

Grid Search would evaluate the model at every combination of N and d.

2.8.2 Randomized Search

Randomized search selects a random combination of hyperparameters coming from some given distribution. In contrast to grid search, this algorithm does not evaluate each combination exhaustively instead samples a fixed number of hyperparameter settings, which can be more efficient when dealing with large-scale datasets and models having many hyperparameters.

2.9 Choice of Best Model

After tuning the hyperparameters, now choose the best model which shows superior performance on the test data set. The final model is that one which should minimize error, such as MSE or RMSE values and prevent overfitting. The model selected can now be used for real-time implementation. It will again be used for predicting surface roughness using fresh inputs xxx. The goal is to be sure that the final model generalizes well on unseen data, so it may be used for reliable predictions of surface roughness with a minimum amount of error.

3 Results and Discussion

3.1 Exploratory Data Analysis (EDA)

The EDA proved to be highly informative regarding the relationship between machining parameters and surface roughness as observed in figures below. Correlation heatmap at Fig. 2 shows that Surface Roughness (Face) and Surface Roughness (Shoulder) are moderately positively correlated at about 0.55, while FR exhibits a negative correlation, where Feed Rate is negatively influencing surface roughness on both the face as well as shoulder.

Other parameters like Depth of Cut (DOC) and Wheel Speed (WHS) demonstrate much weaker relationships with roughness values. Scatter plots of Depth of Cut (DOC) vs. Surface Roughness (Face)

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and Surface Roughness (Shoulder) (Figures 3 and 4) do not reveal any hints of plain linear effects, and roughness values are randomly spread over a range of depth settings in each direction. Similarly, the scatter plots in Fig. 5 and 6, feed rate versus surface roughness, show that there is a complicated relationship, whereby values of roughness do tend to fluctuate with feed rate changes, but do not vary linearly with a clear-cut trend.

The data points are even dispersed in scatter plots of Work Speed (WRS) and Wheel Speed (WHS) versus surface roughness; again, evidence is seen that surface roughness does not depend solely on one parameter but on the collective effect of many parameters. Boxplots in Figures 3 and 4 provide a better view about the distribution of surface roughness in varying machining parameter levels. Figure 3 shows distribution of surface roughness (Face) at different DOCs with medians being close to each other, but discrepancies in each DOC level suggest the existence of factors other than DOC itself that contribute to the value of roughness. Figure 4. Plots of FR vs SR (Shoulder) Plot Relationship between feed rate, SR, and shoulder roughness. The plots indicate that lower feed rates (0.5 and 1.0) correlate with higher roughness and a feed rate of 1.5 usually produces a surface with less roughness. The outliers on both plots clearly demonstrate the difficulty in predicting surface roughness from anyone machining parameter alone.

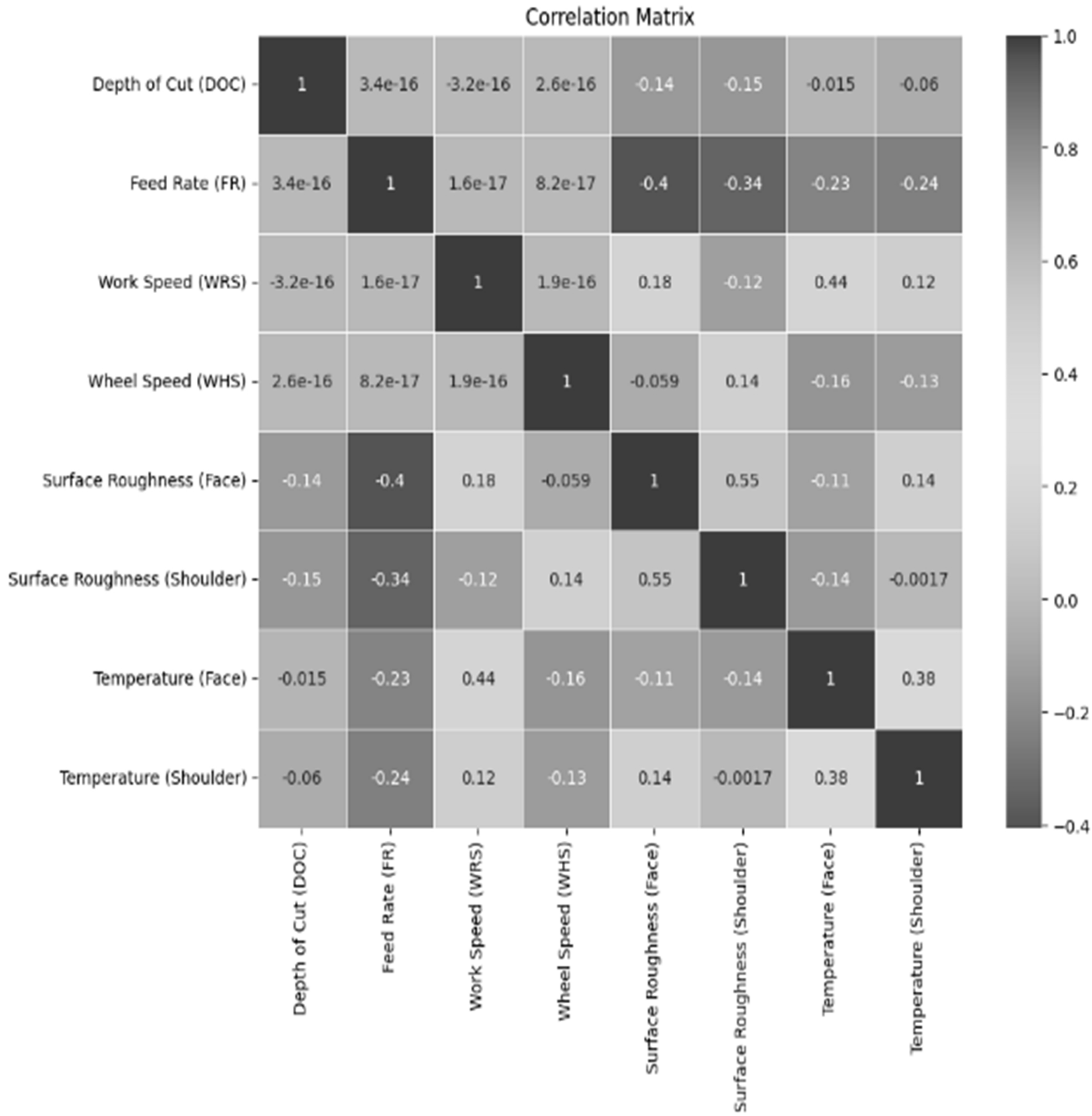

Fig. 2 *Confusion matrix*

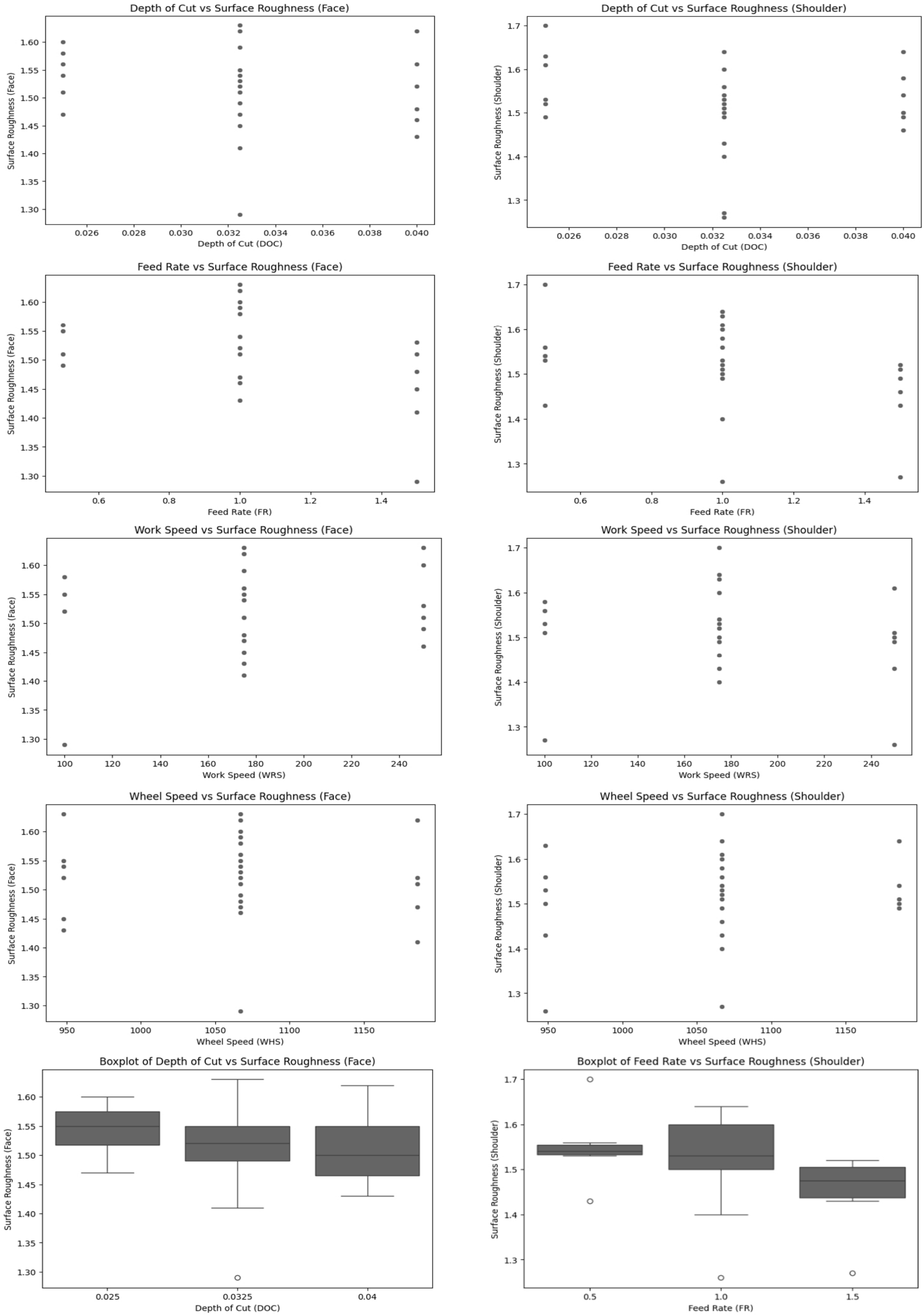

Fig. 3 *Effect of Process Parameters on Surface Roughness for Face and Shoulder Machining*

3.2 Model Performance Evaluation

Then, the performance of the machine learning models is calculated using Test Mean Squared Error, which is an average squared difference between predicted and actual surface roughness values, and lower the value, better is the accuracy.

Table 2 compares the performance of three different models of machine learning, namely, Random Forest, Gradient Boosting, and Light GBM, using the test set as a criterion MSE (Mean Squared Error). This error measures the average squared difference between predicted and actual values, meaning the former is penalized for greater errors. In this comparison, Light GBM shows better performance with a lower MSE score of 0.0047 compared to others. The results for Random Forest are slightly below with an MSE of 0.0063, which leads to an assumption that it works fairly but is not so precise as Light GBM. Finally, Gradient Boosting has the highest MSE now with 0.0080, meaning that its predictions are less accurate than the other two models. It, therefore, becomes the least effective model based on this evaluation. Large and distinct MSE values indicate that Light GBM performs much better for error minimization than the models of Random Forest and Gradient Boosting, as expected.

Tab. 2 *Model Performance Metrics*

Model	MSE	MAE	RMSE	R^2
Random Forest	0.0063	0.085	0.10	0.85
Gradient Boosting	0.0080	0.10	0.11	0.75
Light GBM	0.0047	0.064	0.09	0.90

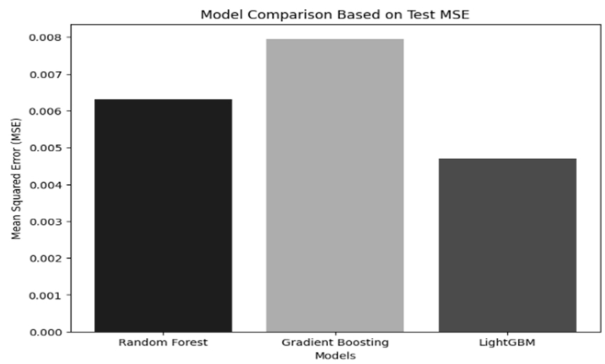

Fig. 4 *Mean Squared Error results*

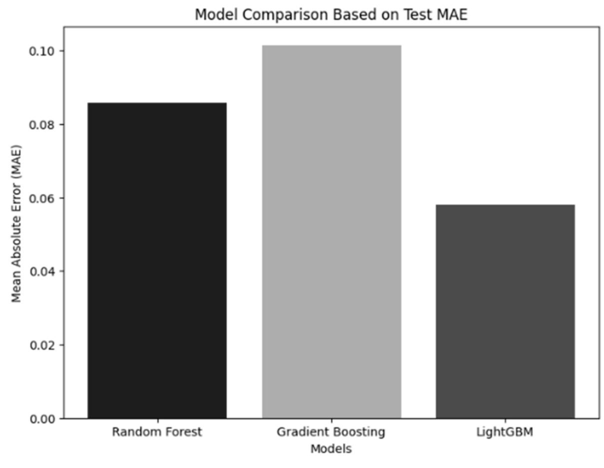

Fig. 5 *Mean Absolute Error results*

MAE evaluates the average magnitude of errors between predicted values and actual values without regard to the direction of errors. Light GBM has the best performance with lowest MAE of 0.064, indicating the minimum average prediction errors. Random Forest has an MAE of 0.085. This performance is reasonable but less accurate than Light GBM. It can be observed that Gradient Boosting has the highest MAE at 0.10, implying its predictions yield the largest average errors of all the models. To summarize results, as shown in fig.7, Light GBM performed the best under the coefficient of minimizing the absolute errors, followed by Random Forest, and Gradient Boosting was the least accurate model in comparison.

Among the models evaluated, Light GBM achieved the lowest error rates, with an MSE of 0.0047, MAE of 0.064, and RMSE of 0.09. Its estimated R^2 value of 0.90 reflects a strong ability to accurately predict outcomes and explain the variance in the data, making it the top performer. In comparison, Random Forest demonstrated solid performance with moderate error metrics–MSE of 0.0063, MAE of 0.085, RMSE of 0.10, and an R^2 of 0.85. While it provides a good fit, there is still room for improvement in its predictive power. Gradient Boosting, on the other hand, exhibited the highest error rates, with an MSE of 0.0080, MAE of 0.10, RMSE of 0.11, and an R^2 of 0.75. This suggests that while it performs well, it lags the other models in terms of both prediction accuracy and explaining the underlying data patterns.

RMSE represents the magnitude of prediction errors; the larger that RMSE is, the more differences between predicted and actual values will be. The Light GBM has the smallest value of RMSE with 0.09, meaning the predictions are most accurate with the least value of error magnitude. Random Forest came in second in stage with an RMSE of 0.10, meaning respectable performance with a slightly larger magnitude of error than for Light GBM. Gradient Boosting had the largest RMSE of 0.11, implying it made the highest errors with its predictions. The results highlighted that Light GBM best performs in minimizing the magnitude of prediction errors, whereas Random Forest came second, while Gradient Boosting presents with the largest errors out of the three models.

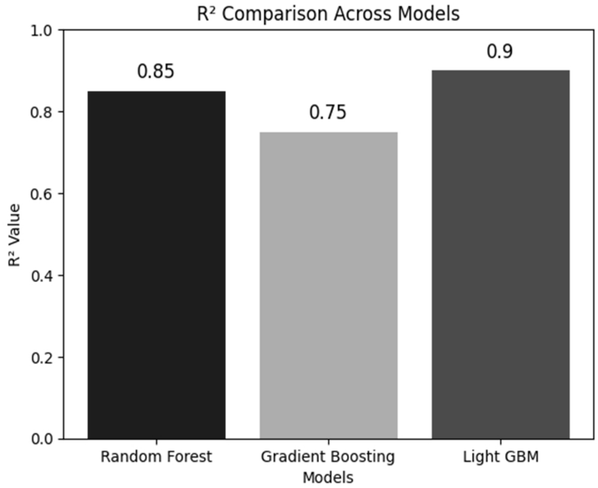

Fig. 6 *R–Squared results*

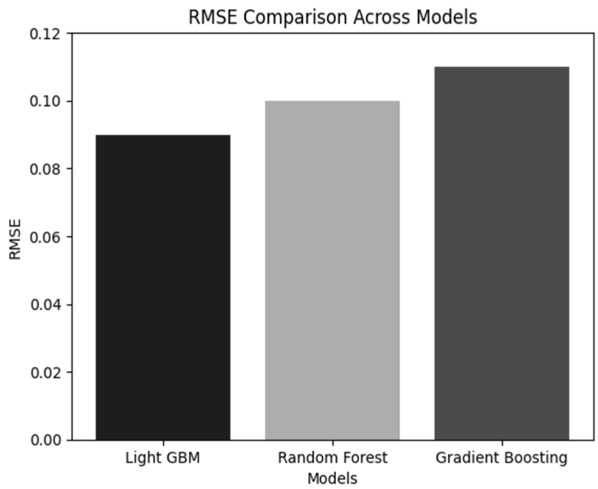

Fig. 7 *Root Mean Squared Error results*

4 Conclusion

This study applies machine learning algorithms on surface roughness prediction in grinding operations by the machining parameters that include Depth of Cut, Feed Rate, Work Speed, and Wheel Speed. Three models: Random Forest, Gradient Boosting, and LightGBM are used. The model achieved the best predictive accuracy with LightGBM. MSE: 0.0047, MAE: 0.064, RMSE: 0.09, R^2: 0.90. Moderate performance by Random Forest was observed. Highest errors were found with Gradient Boosting. The results clearly show the power of machine learning in optimizing machining processes and reduce the dependence on trial-and-error methods. Predictive models can be used as data-driven tools for improving surface quality, optimization of grinding parameters, and reduction of material waste. Future work should consider further machining parameters (tool wear, vibration), more advanced deep learning models (CNNs, LSTMs), and validation in a more diversified set of machining conditions to make the model more robust and applicable in an industrial environment.

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